VYSOKÉ UČENÍ TECHNICKÉ V BRNĚ

Fakulta elektrotechniky
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Bc. Josef Novotný

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DETEKCE NEPOZORNOSTI PILOTŮ

DETECTION OF PILOT INATTENTION

DIPLOMOVÁ PRÁCE

MASTER'S THESIS

AUTOR PRÁCE Bc. Josef Novotný

AUTHOR

VEDOUCÍ PRÁCE prof. Ing. Zdeněk Smékal, CSc.

SUPERVISOR

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Student: Bc. Josef Novotný ***ID:*** 186150
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NÁZEV TÉMATU:

Detekce nepozornosti pilotů

POKYNY PRO VYPRACOVÁNÍ:

Chyba pilota (někdy nazývaná chyba v kokpitu) je termín, který se historicky používá k popisu rozhodnutí, akce nebo nečinnosti pilota nebo posádky letadla, které je určeno jako příčina nehody nebo mimořádné události. Termín zahrnuje chyby, přehlédnutí, mezery v úsudku, mezery ve výcviku, nepříznivé návyky a selhání při náležité péči v povinnostech pilota. Příčiny chyby pilota zahrnují psychologická a fyziologická omezení člověka. Úkolem diplomové práce je charakterizace vlastnosti nepozorného chování pilotů, navržení vhodné metody pro parametrizaci těchto událostí, volba vhodných senzorů pro jejich detekci a porovnaní způsobů detekce pomocí metod strojového učení.

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[2] GOODFELLOW, I., BENGIO, Y. and COURVILLE, A., 2016. Deep learning. MIT press.

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Vedoucí práce: prof. Ing. Zdeněk Smékal, CSc.
Konzultant: Ing. Hicham Atassi, Ph.D. (Honeywell)

prof. Ing. Jiří Mišurec, CSc.
předseda rady studijního programu

ABSTRACT

This master thesis deals with the issue of pilot inattention and proposes a design of a system for detecting inattention of general aviation pilots. Inattention belongs to one of the human-caused errors that currently contribute to the most common causes of aviation accidents. The theoretical part deals with the definition of inattention, compares different aviation categories based on flight rules, and contains a search of detection methods. The practical part of the work deals with the selection of suitable sensors, data collection, and implementation of detection algorithms. In this thesis, two different approaches were chosen. The first implementing machine learning using the RUSBoost classifier, which detects states of attention and distraction. The second approach represents the design of a system for detecting pilot inattention based on a set of rules specified in the CLIPS expert system.

KEYWORDS

artificial intelligence, CLIPS, expert system, machine learning, machine reasoning, pilot inattention, RUSBoost

ABSTRAKT

Tato diplomová práce se zabývá problémem nepozornosti pilotů a návrhem systému pro detekci nepozornosti pilotů všeobecného letectví. Nepozornost patří mezi chyby způsobené lidským faktorem, které v současné době přispívají k nejčastějším příčinám nehod v letectví. Teoretická část práce se věnuje definici pojmu nepozornosti, srovnává různé kategorie letectví na základě letových pravidel a obsahuje rešerši detekčních metod. Praktická část práce se zabývá výběrem vhodných senzorů, sběrem dat a realizací detekčních algoritmů. V rámci řešení byly zvoleny dva různé přístupy. První z nich představuje implementaci metody strojového učení s využitím RUSBoost klasifikátoru, který detekuje stavy pozornosti a rozptýlení. Druhý přístup reprezentuje návrh systému pro detekci nepozornosti pilotů na základě souboru pravidel specifikovaných v expertním systému CLIPS.

KLÍČOVÁ SLOVA

umělá inteligence, CLIPS, expertní systém, strojové učení, strojové usuzování, nepozornost pilotů, RUSBoost

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ROZŠÍŘENÝ ABSTRAKT

Nepozornost je považována za negativní jev, který ovlivňuje celou řadu činností, které vyžadují vysokou míru soustředěnosti. Pilotování letadla je jednou z aktivit, kde pozornost hraje klíčovou roli. Nezbytnými předpoklady každého pilota je dostatečná pozornost a schopnost adekvátně reagovat na vzniklou situaci. Nejvíce problematicky se jeví nepozornost zejména v rámci všeobecného letectví, kde možná absence kopilota a dalších bezpečnostních prvků letadla představují vyšší riziko pro vznik lidské chyby. Tato diplomová práce se zabývá nepozorností pilotů všeobecného letectví a navrhuje dva možné způsoby řešení. První z nich využívá metody strojového učení, druhý přístup pak navrhuje systém detekce nepozornosti s využitím expertního systému. Práce je rozdělena na teoretickou část, která definuje základní pojmy týkající se nepozornosti, srovnává jednotlivá letová pravidla a dále zahrnuje rešerši současných metod řešení. Navazující praktická část této práce se zabývá výběrem senzorů, sběrem dat a implementací detekčních metod z oblasti umělé inteligence. Jedná se o využití metody strojového učení, kterou představuje implementace RUSBoost klasifikátoru umožňující detekovat stav pozornosti a rozptýlení. Druhá navržená metoda představuje řešení na základě strojového uvažování a využívá pravidel definovaných v rámci expertního systému CLIPS.

V první části práce je specifikován rozsah oblasti nepozornosti, kterým se tato diplomová práce zabývá. S odkazem na statistiku [1] je nejvíce leteckých nehod vykázáno v odvětví všeobecného letectví a patří tak k nejvíce rizikovým odvětvím. Všeobecné letectví zahrnuje veškeré aktivity vyjma komerčních letů a dále se dělí podle letových pravidel na dvě hlavní kategorie. Jedná se o lety podle přístrojů IFR a lety za viditelnosti VFR. Obě kategorie jsou specifické odlišnými letovými pravidly, které ovlivňují i chování pilota. Let za viditelnosti VFR umožnuje vést let pouze za vyhovujících meteorologických podmínek. Pilot se při takovém letu orientuje pouze výhledem z kabiny a řídí se pravidly pro visuální let. Naproti tomu, let podle přístrojů umožňuje i let za horších meteorologických podmínek. Pilot letadla se řídí na základě údajů přístrojů a nikoli výhledem z kabiny. V rámci práce byla obě letová pravidla srovnána s piloty obou letových kategorií. Na základě zjištěných informací bylo rozhodnuto se věnovat kategorii IFR. Jedná se totiž o oblast letectví, která je náročnější na pozornost pilota a schopnost vyhodnocovat situaci pouze na základě údajů z letecké avioniky. Piloti IFR jsou tak náchylnější k riziku vzniku nepozornosti, v jejímž důsledku může docházet až ke ztrátě orientace v prostoru.

Dále práce představuje rešerši metod, které se zabývají detekcí nepozornosti pilotů a řidičů. Na základě této rešerše byly specifikovány nejdůležitější charak-

teristiky pro detekci nepozornosti. Mezi ty patří zejména pohyby očí a hlavy. Za účelem měření těchto charakteristik byly vybrány vhodné senzory, a to především systém pro sledování očí, který detekuje oční charakteristiky jako jsou například fixace, sakády, směr pohledu očí, pozice hlavy a další. Rešerše také zahrnuje srovnání přesnosti detekce rozptýlení řidičů v rámci využití metod strojového učení. Jako nejvhodnější se jeví využití dat ze systému pro sledování očí a aplikace metod strojového učení s učitelem. Dále z nabízených metod v rámci rešerše je navržen alternativní přístup pomocí definice souboru pravidel.

V rámci praktické realizace byly nejdříve vybrány senzory pro uskutečnění sběru dat. Tyto senzory zahrnují systém pro sledování očí, chytrý náramek, všesměrový mikrofon a sluchátka s připevněným inerciálním senzorem a mikrofonem. Dále byl připraven scénář pro sběr dat, který zahrnoval instrukce pro účastníky experimentu s minimálními leteckými zkušenostmi. Tento scénář obsahoval jednotlivé aktivity přispívající k pozornosti či rozptýlení. Na jejímž základě byl proveden sběr dat ve statickém simulátoru. Naměřená data byla vyhodnocena a bylo provedeno trénování klasifikátoru pomocí metody RUSBoost pro detekci stavu pozornosti a rozptýlení. Algoritmus při využití dat v kombinaci systému pro sledování očí a chytrého náramku dosahoval nejvyšší přesnosti, a to 87 %. Nicméně toto řešení je problematické integrovat v reálném prostředí kokpitu letadla. Dále bylo zjištěno, že v případě využití inerciálního sensoru v kombinaci s náramkem je možné dosáhnout přesnosti klasifikátoru 77,1 %. Z hlediska praktické realizace kombinace náramku a inerciálního senzoru poskytuje dobrý poměr cena-výkon, který je možný nadále zlepšovat pří využití většího množství dat. Nicméně další pokračování experimentálního měření bylo přerušeno z důvodu nepříznivé pandemické situace, a tak aplikace metod strojového učení nebylo možné dále rozvíjet.

Alternativním přístupem byl návrh systému pro detekci nepozornosti pilota na základě definice souboru pravidel. Jedná se o detekční systém, který využívá expertní systém CLIPS, který patří do kategorie metod strojového uvažování. V rámci expertního systému bylo dále nezbytné definovat pravidla, a to zejména na základě výsledků uvedených studií. Vstupní data do systému bylo dále nutné parametrizovat do symbolické notace vhodné pro účely expertního systému. Systém byl evaluován za využití stejných dat ze senzorů jako u metod strojového učení. V rámci expertního systému se uplatňují definovaná pravidla, která implikují nová fakta o rysech chování a aktivitách. Na základě rozhodovacího mechanismu byly aktivity vyhodnoceny v rámci 30sekundového časového okna. Výsledkem tohoto systému je skóre pozornosti, pohybující se v rozsahu -100 až 100, kde záporné hodnoty reprezentují nepozornost a kladné hodnoty pak pozornost. Systém detekce nepozornosti pilota je dále prezentován v rámci demonstrační platformy, která ilustruje chování expertního systému a poskytuje přehled vazeb mezi implikovanými fakty a skórem pozornosti.

V této diplomové práci bylo potvrzeno, že expertní systém je vhodným řešením, zejména díky transparentnosti a snadné rozšiřitelnosti o další fakta a pravidla, která mají srozumitelnou symbolickou notaci. Výhodou přístupu založeného na definici souboru pravidel je především dobrá vysvětlitelnost pro další ladění systému. Tuto metodu je tak možné dále rozvíjet s využitím dat z více senzorů představující jednotlivá fakta. Další možným krokem může být i například kombinace metody strojového učení ke specifikaci jednotlivých dílčích činností a tím tak začleněním dalších faktů. Dále je i možné definovat větší soubor pravidel o další znalosti expertů v dané oblasti.

DECLARATION

I declare that I have written the Master's Thesis titled "Detection of Pilot Inattention" independently, under the guidance of the advisor and using exclusively the technical references and other sources of information cited in the thesis and listed in the comprehensive bibliography at the end of the thesis.

As the author I furthermore declare that, with respect to the creation of this Master's Thesis, I have not infringed any copyright or violated anyone's personal and/or ownership rights. In this context, I am fully aware of the consequences of breaking Regulation § 11 of the Copyright Act No. 121/2000 Coll. of the Czech Republic, as amended, and of any breach of rights related to intellectual property or introduced within amendments to relevant Acts such as the Intellectual Property Act or the Criminal Code, Act No. 40/2009 Coll., Section 2, Head VI, Part 4.

Brno ....

author's signature

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Contents

List of Figures

List of Tables

Introduction

Inattention affects many professions that require a high level of concentration. Vigilance, alertness, and sustained attention play a significant role in aviation safety. Loss of attention is considered as a dangerous phenomenon, which may arise unexpectedly during all phases of flight. Pilot inattention contributes to the errors caused by the human factor. According to the statistics reported in [1] [2] [3], air accidents caused by the human factor prevails. General aviation pilots are especially at higher risk of inattention due to the possible absence of additional flight crew members. This work aims to propose methods for pilot inattention detection, which might be an enabler for further mitigation strategies, such as alerting the pilot or activating certain automated procedures.

The master thesis is structured as follows: Chapter 1 formulates the background of the inattention and its various causes. These include inattention caused by distraction effects or by human limitation. In chapter 2, the comparison of IFR and VFR flight rules is presented. This chapter contains valuable expertise provided by pilots. Chapter 3 introduces the state-of-the-art solutions. Reviewed studies cover visual, auditory, and cognitive distractions and demonstrate the use of various sensors to detect inattention. Moreover, studies deal with the inattention of general aviation pilots, drivers, and inexperienced participants. Based on the state-of-the-art findings, it was decided to use machine learning, described in chapter 4. Chapter 5 further introduces expert system, which is considered as a second approach for the development of a pilot inattention detection system.

The practical part of the thesis deals with the design of a pilot inattention detection system. Based on the knowledge from the state-of-the-art, two approaches were proposed, namely machine learning and the system based on an expert system. Both approaches required data collection, referring to the chapter 6. The following steps cover the selection of suitable sensors and designing a data collection protocol. Chapter 7 outlines a process of data collection. The obtained data were further analyzed and used for machine learning RUSBoost classifier, presented in chapter 8. Identical data were also used for a pilot inattention detection system based on the expert system, described in chapter 9. As a final step, both approaches were evaluated and compared.

In fig. 1, the Gantt diagram outlines the progress of this work, the time required for each task, and the most important milestones.

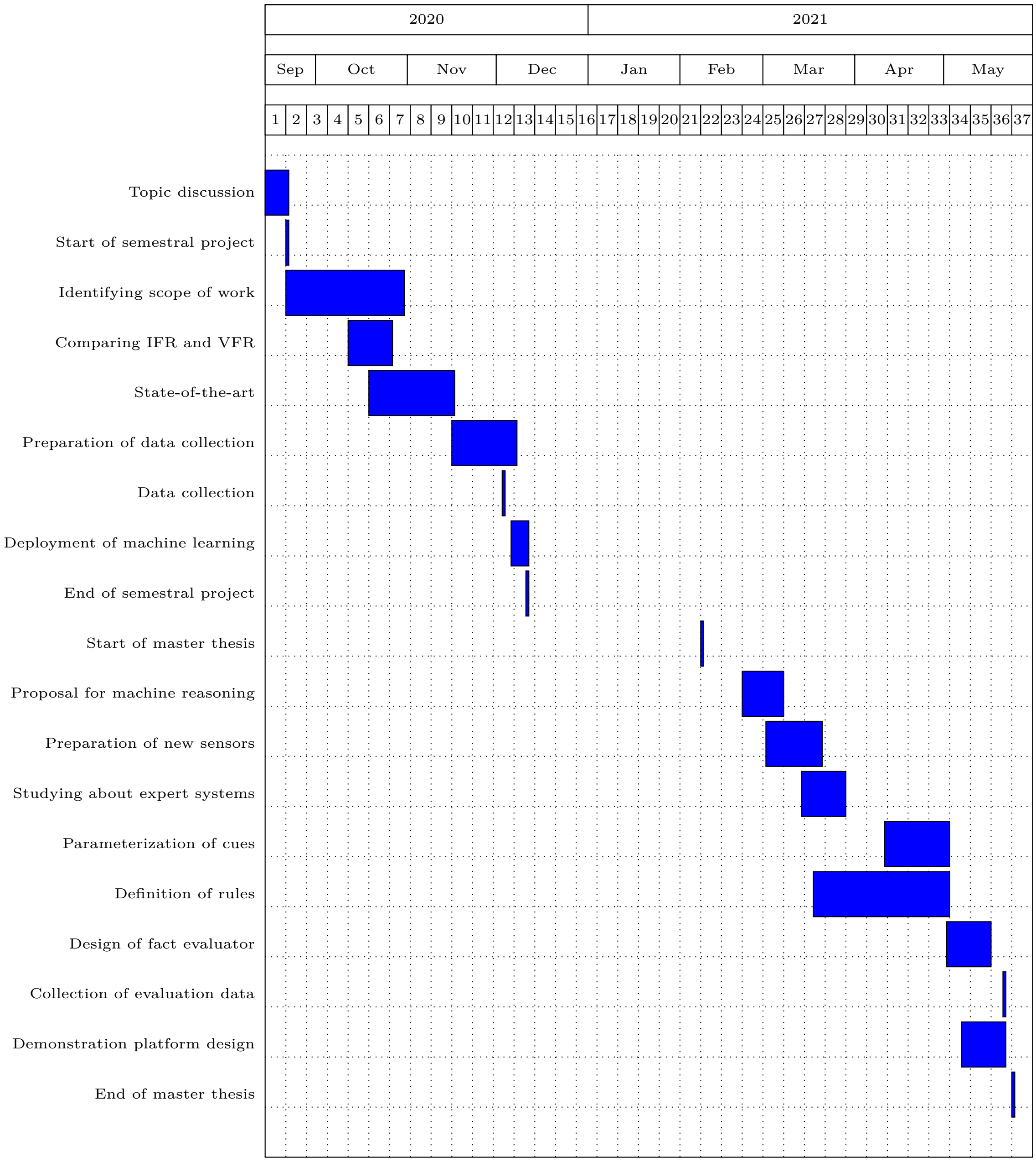

Fig. 1: The Gantt progress chart of the master thesis.

1 Background

Piloting an aircraft is a complex, multi-task activity. Aside from flying an aircraft safely, pilots have to perform other flight-related tasks concurrently. They have to communicate with air traffic controllers (ATC), manage the autopilots, read and interpret a wide range of data, navigate, and concentrate on dozens of other things. Concisely, they have to manage the ability to pay attention to many different systems all at once.

According to recent studies [2] [4] [5], several factors may affect inattention. It can be either by a cognitive impairment, loss of situation awareness, or high workload. The term of pilot inattention is also associated with the concept of distraction. Therefore, the scope of the problem will be specified in the following sections.

1.1 Problem definition

In general, the pilot's inattention belongs to the errors caused by the human factor, which refers to a complex issue and requires understanding the background of the aviation problems and their impact on today's aviation world. Besides the human factor, accidents were in the past caused predominantly by a technical problem. Over the years, efforts to improve mechanical parts have always been the most crucial to ensure safe aviation. The level of aviation safety has significantly increased, and the accident rate decreased. The relative proportion of human factor-related accidents is steadily growing, as shown in fig. 1.1. [2]

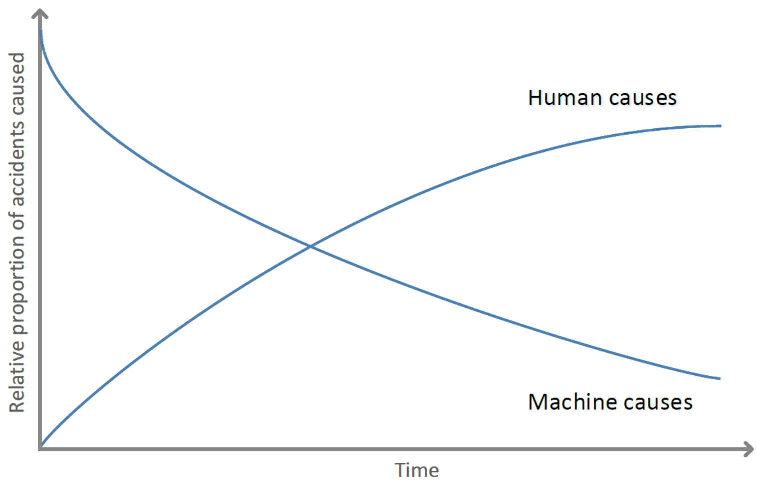

Fig. 1.1: Trends in accident causation. [2]

Compared to the past, nowadays human factor accidents prevails. This trend evolved from around 20 % in the 1960s to the 80 % in the 1990s. The human factor became the leading cause of today's aircraft accidents. The previous statistics from literature [2] gives us a general overview of the main cause of accidents in all aviation sectors. According to Eurostat [1], most of the aviation accidents in 2019 were registered in the category of general aviation (GA). Overall, 81 % of GA aviation fatalities were caused by human error. Contrary, commercial air transport accidents resulted in 9 % of all fatalities. It means that the human factor has more significant consequences for the GA sector.

The diversity of GA is so comprehensive that the International Civil Aviation Organization (ICAO) defines GA operation by exception. Referring to ICAO [6], GA is defined as *"all civil aviation operations other than scheduled air services and non-scheduled air transport operations for remuneration or hire"*. This category encompass a wide rannge of activities, including the following:

- Corporate Aviation
- Business Aviation
- Personal / Private Travel
- Air Tourism
- Recreational Flying
- Air Sports

For example, GA flights include company own-use flight operations, flights for business purposes, travel for personal reasons, leisure flying activities, or air sports. The significance of GA becomes greater since every commercial air pilot must begin their journey to professional competence in the cockpit of a GA aircraft.

In conclusion, the GA sector is the most common category and the riskiest aviation sector at the same time. It is due to several factors, primarily due to the absence of a backup engine and co-pilot. Modern airliners also have more safety features than private GA aircrafts. In summary, GA is more prone to accidents caused by human error. The following work will therefore focus mainly on the problems associated with GA flying.

1.2 Aim and scope

The work aims mainly on the inattention of GA pilots. The reason is that GA pilots' inattention manifests statistically more often, and the GA sector is more prone to have fatal consequences. According to the paper [7], the issue of inattention can be divided into the following categories, depending on the cause, as tab. 1.1 makes clear.

Human limination	External factors	Organizational factors
Over-reliance on automation	Lack of communication	Lack of teamwork
Inattentional blindness	Fatigue	Norms
Inattentional deafness	Stress	Lack of resources
Lack of assertiveness	Distraction	Lack of knowledge
Lack of awareness		Pressure

Tab. 1.1: Aviation human factors. [7]

The scope of work is to define inattention as a problem of the human factor, find suitable sensors that can parameterize measurable events indicating inattention, and use machine learning and machine reasoning to detect these events.

In order to define the issue of inattention, it is necessary to determine the exact area that the work will deal with. The issue of inattention is bind primarily with the lack of situation awareness. As reported in [7], up to 85 % of all human factor accidents are caused by the insufficient perception of elements in the flight environment. Situation awareness is obtained by scanning the environment and comparing the gathered information with mental models. Therefore, a standard pilot behavior model includes, besides task of flying also communication, coordination, objective setting, and feedback to the situation. The problem of human limitation also involves inattentional blindness and inattention deafness.

The second cause of pilots' inattention presents an external factor represented by the effects of distraction. Distraction often occurs when the mind is away from the primary task of flying. It occurs when pilots' attention shifts away from the original focal point. It can be either visual, auditory, or cognitive, as will be discussed further.

1.3 Inattention

According to the literature published by Berlyne [8]: *"Attention is conceived as a focusing response to a stimulus or task that reflects a state of arousal or concentration"*. Contrary to term of attention, inattention is represented by pilot's selection of improper target or diminishment of attention to critical activities for safe flight. Such a state may occur whenever a pilot has a low vigilance. This might be caused by multiple reasons, as reported in literature [9]:

- Biological restricted attention
  - flight related distraction
  - non-flight related distaction
- Neglected attention
- Diverted attention
- Cursory attention
- Misprioritized attention

Biological restricted attention

Performance of each individual is closely related to the arousal level, as illustrated in fig. 1.2. Pilots with a low level of arousal may be easily distracted and have a higher tendency to engage in unnecessary tasks. The other end of the range shows when a pilot is overloaded, and mental activity reaches its limit. As a result, the likelihood of further mistakes is increased as well. [10]

Misprioritized attention

Piloting an aircraft requires the performance of the task in the correct order regarding its priority. The basic pilots' rule of thumb says: to aviate, to navigate, to communicate. This axiom teaches pilots that fly the aircraft is the first and the main important task. Misprioritized attention includes situations in which are preferred activities with a lower priority. For example, pilots may be prone to skip the basic instruments, such as an attitude indicator, during responding to ATC. Pilots psychologically tend to misprioritize tasks more frequently when the interruption involved a communications task, as stated in study [4].

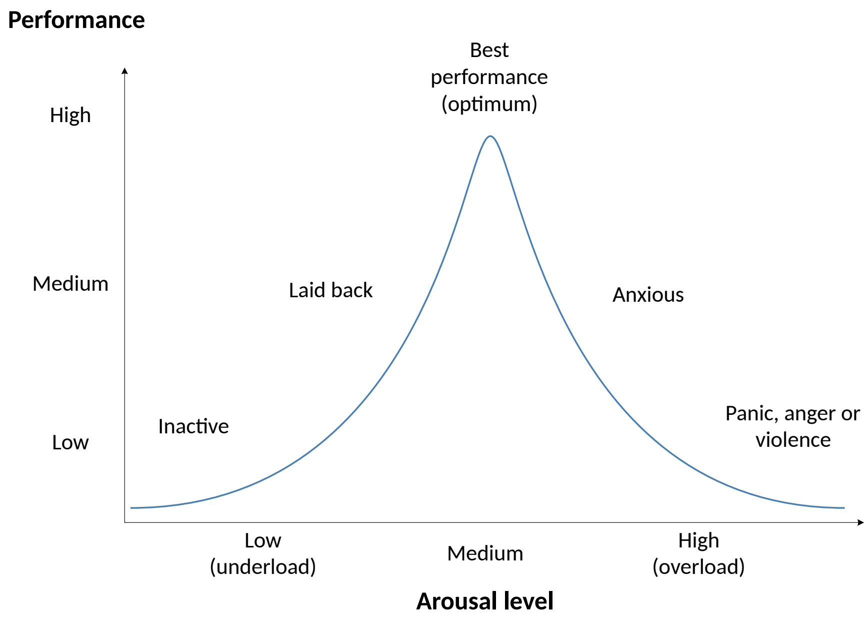

Fig. 1.2: Illustration of human performance curve. [10]

Neglected attention

The ability of the human brain to give attention to certain stimuli is indispensable during flight. However, full concentration can also lead to inattention. It is not desirable that the pilot will get into a condition called inattentional blindness. As reported in the literature [11], the strong human mechanism during deep concentration is trying to stop attention from mind fragmentation. If the person is giving too much focus to one stimulus, the brain tends to neglect even very obvious events. As an example, it may lead to a neglected reaction to a warning alarm.

Cursory attention

Cursory attention is identified as an omission of a task primarily due to time pressure. This can lead to the omission of proper scanning routine and cursory performance of important tasks, such as checklist procedure. This kind of inattention is especially relevant for airline pilots.

Diverted attention

The category of diverted attention discusses the issue of giving attention to the secondary activity, either flight-related or non-flight-related, as described in literature [9]. During the flight, pilots have to deal with many flight-related activities. For example, it is presented by a head-down activity such as checklists or programming the flight management system (FMS). In such situations, the pilots' eyes are diverted, and they may lose attention from more important tasks. The second category describes non-flight-related diverted attention, which can occur by the use of portables or cameras. It also includes cognitive distraction as an irrelevant conversation, day-dreaming or mind-wandering.

In summary, attention is conceived as a limited resource. According to [5], it has been shown that sudden and unexpected stimulus can divert attention irrespectively to the primary task. Oppositely, the pilot also may be prone to ignore expected and relevant stimuli.

1.4 Situation awareness

Pilot inattention can consequently lead to loss of situation awareness. The term of situation awareness (SA) is more specific. In addition to attention, SA includes the full scope of knowledge and context of the operational environment. The concept of SA specifies the desired attention. It emphasizes correct perception and interpretation of the current situation concerning future states. SA is recognized as a critical basis for successful decision-making in a wide range of situations. According to the Endley [12], situation awareness can be theoretically described using a causal model, as shown in fig. 1.3. This model supports inferences about causes and consequences. Endley's model illustrates three levels of SA:

- Perception
- Comprehension
- Projection

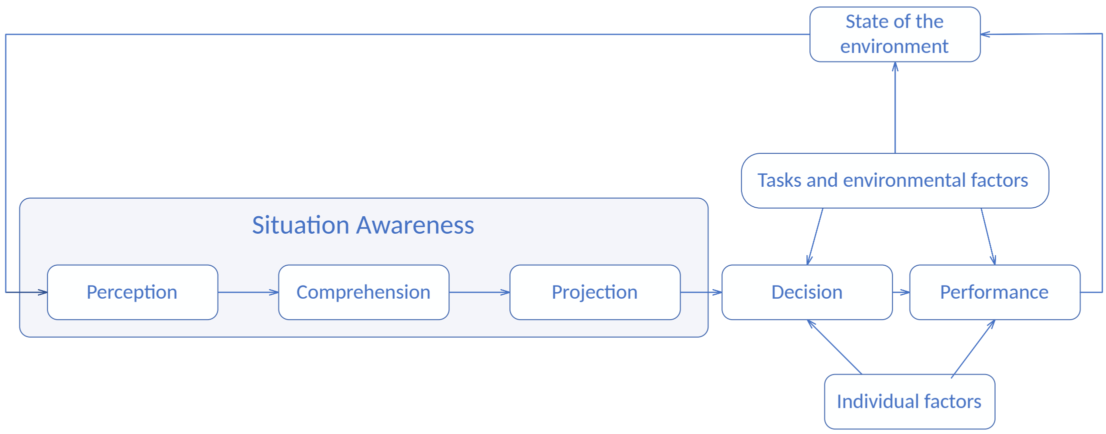

Fig. 1.3: Endsley's model of situation awareness. Inspired from [12].

Perception

The first step to achieving SA is the correct perception of the relevant elements' state, attributes, and dynamics. It is the most basic level that includes simple recognition, which leads to an awareness of multiple elements, such as instruments, systems, and situations.

Comprehension

Next step in achieving SA involves a synthesis of elements from the perception stage through interpretation and evaluation. At this level of SA, pilots have to understand the impact of their objectives. This involves developing a comprehensive overview of the situation.

Projection

The highest level of SA means the ability to plan future action based on the previous stage of knowledge. It is achieved through knowledge of the status and dynamics of each element. This manifests by the pilot's ability to extrapolating the information forward in time and determine how it will affect the future states.

1.5 Distraction

Following the previous chapter, distraction is one of the causes of inattention. Distraction is defined by Macquarie [13] as *"the act of distracting, drawing away of diverting, an action that dived attention"*. Pilot distraction might be defined as a process that takes a pilot's attention away from the task of flying. The definition of each distraction should be conceptualized within the context of attention, as illustrated in fig. 1.4. Distraction can be either flight-related, as a reaction on an element with lower priority, or non-flight-related. A secondary task can be triggered either as an internal psychological stimulus, such as cognitive distraction, or an external stimulus, as a visual and auditory distraction.

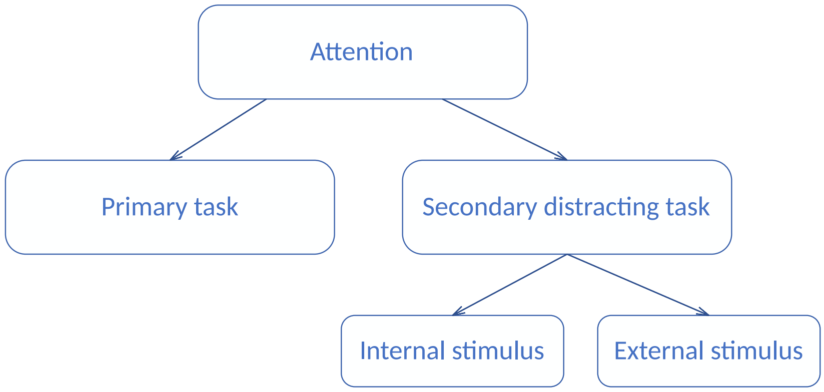

Fig. 1.4: Distraction as a part of attention schema.

The effect of distraction is surmised as an interruption of pilot control. Pilots generally deal with distraction as a regular part of flying and can arise unexpectedly during all phases of a flight. Pilots are vulnerable to distraction, which sources are diverse and divided according to report [5] into the following categories:

- **Visual distraction** represented by looking away from primary task, use of portables, reading from maps
- **Auditory distraction**, which can be found during an active conversation with crew or by multiple sound of warning tones.
- **Cognitive distraction**, presented as mind-wandering, focusing on a specific topic, or being lost in thought.

2 Flight rules

Regulation of civil aviation [14] distinguishes between Visual flight rules (VFR) and Instrumental flight rules (IFR). These two sets of rules give specific regulations for each sector. It follows that these two different categories involve different sources of distraction.

2.1 Visual Flight Rules

Visual flight rule (VFR) indicates a specific rule when pilots fly mostly by looking out of the window. This type of rule requires minimum visual meteorological condition (VMC), which is a set of limitations that specify visibility requirements. The basic of VFR determines pilot's ability to aviate and navigate the aircraft only with reference to external cues. ATC is not responsible for keeping VFR airplanes separate but only provides necessary information about traffic. [15]

VFR pilot's view

VFR rules are very limiting for meteorological conditions. It means that it is not possible to fly in all weather conditions. However, the pilot must have good observation skills and vigilance. A pilot is only responsible for monitoring spacing between airplanes. In terms of behavior, VFR piloting can be likened to driving a car, which also requires full vigilance towards the surroundings. All points from the discussion is summarized in the following tab. 2.1.

Issue	Response
Advantage of VFR	Peripheral vision, similar attention distribution as driving a car
Disadvantage of VFR	Strict rules restrict flying in bad VMC, stress during change of VMC
Standart behavior	Situation monitoring out of the cocpit
Negative behaviour	Long fixation, reading, converse
Distractions	Accustic and visual alerts (fuel, air speed, gear malfunction), portables, maps, checklists, change of VMC
Interest in project	Highly interested
Criticism	Inattention is treated by strict VFR rules
Technical problems	The boundary between distraction and attention can be too narrow.

Tab. 2.1: Comprehensive summary of VFR based on the expertise of pilot

2.2 Instrumental Flight Rules

Instrument flight rules (IFR) represent a set of rules for flying an aircraft in instrument meteorological conditions (IMC) or at night. IMC is a condition below the minimums for VFR flying. In contrast, the pilot scans the instruments, which provide all flight information. Generally, pilots are able to navigate a plane through rough weather conditions using cockpit instruments as altimeters, GPS systems and vertical speed indicators. [15]

IFR pilot's view

The main advantage of IFR is the ability to fly in almost any weather. For a pilot, the IFR flights are more demanding due to the necessary experience. Pilots orient themselves only with the help of flight instruments. There is a risk of loss of situation awareness. However, this flight rule involves more risks, such as insufficient scanning of instruments or poor prioritization of tasks. The discussion with the pilot was rather critical, as skepticism prevailed over the algorithmic description of the pilot's behavior. The exact pilot behavior can not be determined, as it varies depending on the situation and experience of the pilot. The whole points of the discussion are summarized in the tab. 2.2.

Issue	Response
Advantage of IFR	No restrictions due to unsufficient VMC
Disadvantage of IFR	Essential pilot training and experience, threat of lack of SA, attention overload
Standart behavior	Scanning of flight instruments
Negative behaviour	Long fixation, looking out of the cockpit, misprioritization of tasks
Distractions	Accustic and visual alerts (fuel, air speed, gear malfunction), portables, maps, checklists, tasks overload
Interest in project	Rather skeptical
Criticism	The attention detection device should not overload the pilot in critical moments.
Technical problems	Some types of inattention (misprioritized) are difficult to detect.

Tab. 2.2: Comprehensive summary of IFR based on the expertise of pilot.

3 State-of-the-art

This chapter introduces the key concepts and research in the field of inattention. It deals with a literature review about various detection methods. It covers inattention detection of drivers, pilots, and inexperienced participants. These studies compare different areas of application, different sensors, and applied methods. Several methods are reported in the following state-of-the-art review to address this issue.

3.1 Measurements of attention using eye track

The use of an eye-tracking system is one of the most common approaches for attention detection. The vast majority of studies involve either eye-tracking glasses or a camera, which is the most widely used sensor for measuring attention. According to several researches [16] [17] [18] [19], the usage of such system is primarily focused on detecting attention during instrumental IFR flight or approach. This category is the most interesting in terms of complexity. IFR pilots have to deal with various activities during the flight. At the same time, the activity is well quantifiable through the eye-tracking system.

The first presented approach [16] deals with pilots' behavior during critical phases of IFR flights. This work aimed to evaluate the eye movement statistically and find characteristic attention distribution during the precision (ILS) and non-precision (NDB) approaches. The crucial values for estimating the correct scanning techniques were fixation time and dwell time. Another objective was to monitor the area of interest, as evident from fig. 3.1.

Fig. 3.1: Distribution of fixation during approach. [16]

The finding of this study is that experienced pilots have a specific radially selective scanning technique on the flight instruments. It is characterized by short dwell time. In more precise terms, experienced pilots are able to perform 120 – 140 saccades per minute, compared to inexperienced pilots. Their value reaches only about 100 - 120 saccades per minute. Saccades are rapid movements between two fixations. A higher value of this parameter indicates more experience and better situation awareness. Among others, fixation distribution differs for each phase of flight. An example is a percentage of gaze on an altimeter during the approach. Individual flight instruments are scanned with different importance. Consequently, the average fixation times are also not fixed but determined by the need in a particular flight phase. According to these characteristics, reported in [16], it is possible to distinguish between novice and experienced pilots. The novice pilots tend to omit the primary flight instruments (fig. 3.2), while an experienced pilot tries also to control secondary instruments, which results in a higher frequency of saccades.

Fig. 3.2: Deployment of the instruments on the instrument panel of the aircraft Beechcraft Super King Air B200.

3.2 Pilot situation awareness monitoring

Study [17] focused on a rule-based approach to assess novice and experienced pilots. The pilot's ability to obtain and adequately process information from various sources is essential for safe flight operation. If the pilot's perception is affected by some distraction, it might lead to losing attention. A pilot's situation awareness can be assessed by monitoring the behavior using observation of the eye movement by a rule-based evaluation system. An example is a visual inattention characterized by different scanning patterns in case of blurring or misplaced attention, as shown in 3.3.

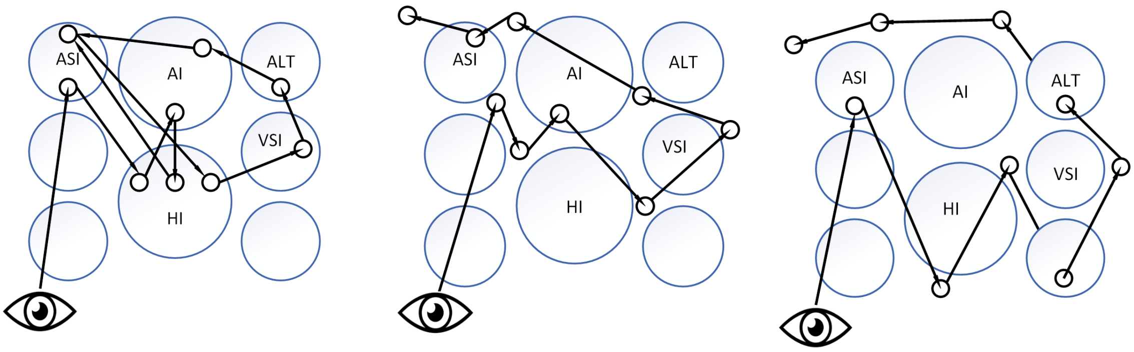

Fig. 3.3: Illustration of various attention patterns. Attention focusing (left), attention blurring (center), and misplaced attention (right). Adapted from [17].

Firstly, behavior patterns from the experienced pilot were obtained as a baseline model. Such behavior may vary depending on pilots, although they have several characteristics in common. It might be a task sequence or a similar dwell time. The gaze analyzer outputs were dwell time, elapsed time, and total fixation time on each instrument. The main parameters that were observed in the scanning pattern of an experienced pilot were:

- average fixation time on each instrument
- scanning frequency
- tasks/instruments sequence
- rate of change

One of the aforementioned sign of correct perception is a fixation time. It has been shown in [17] that it required between 200 ms and 600 ms to perceive information correctly, as illustrated in fig. 3.4. This information contributes to the general situation awareness model in relation to the information about which instrument was scanned, when was the last scan, and how long an instrument was not observed.

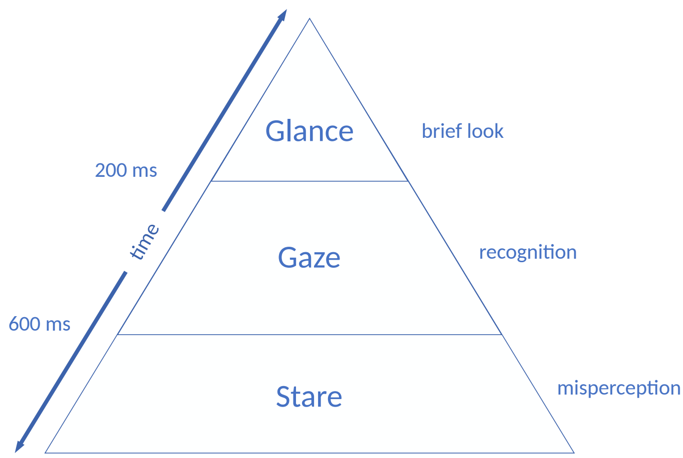

Fig. 3.4: Fixation duration classification [17].

Early warning of loss of situation awareness can be beneficial to prevent the potential risk of an accident. However, real-time cockpit situations may differ, and if unusual behavior patterns are found only once, it does not necessarily lead to loss of situation awareness. The presented study [17] takes in account potential deviations and alerts just in case that unusual behavior patterns are repeated, or there are found multiple factors for the state of inattention. Similarly, behavioral differences might also be observed by measuring heart rate, brain waves, and facial expressions. Though, these approaches are intrusive methods and are generally regarded as not feasible in real conditions.

3.3 Computer-aided assessment of attention

Computer-aided assessment represents an alternative way of evaluating inattention. The research [19] deals with the inattention of aviation pilots and inexperienced participants and compares their behaviors. The focus of research has been aimed at measuring and evaluating the attention of pilots' candidates. This solution is used to select the most promising candidates and identify the key factors that should be improved in the following training.

This study involves a set of seven computerized tests, which are described below in tab. 3.1. They are designed to evaluate the performance of pilots and untrained participants as a control group. The test defines reaction time, which elapses time from the appearance of the stimulus to the reaction. Besides correct reaction, the error and omission rate are also measured.

The first test assesses purely psycho-physiological attention to randomly proposed stimulus in central and peripheral view. The second task deals with multiple searches and consists of the search and identification of random targets. Color discrimination deals with direct color recognition. Color-word inference indicates a color that appears filled with a different color. These represent a test of resistance to distraction factor. The experiment also includes ground interference, which tests the ability to discriminate a target from the background through peripheral vision. It resembles the real situation in the cockpit at the time of scanning the flight instruments during the flight duty.

Consequently, the presented research focuses on diverted attention, which may occur during two parallel tasks, such as visual search and auditory recognition. It simulates a usual duty of a GA pilot in the typical situation when should pay attention to flight instruments and simultaneously follow instructions from the ATC. A further test, a digital span, assesses the available working memory capacity that has been recognized as a fundamental component of the pilot's attention. It involves the integration of incoming information into the pilots' SA model. Last but not least, the test of global vision was performed. This test evaluates the interference with moving targets in different locations. Table 3.1 summarizes a set of tests and result from t-test comparison. The t-test comparison aimed to verify the hypothesis that pilots and control groups are two independent samples. Negative values of t were in favor of the pilot group. All test contains at least one variable that rejects the hypothesis with statistical significance ($p < 0.01$). As noted in the following table from the literature [19], the best result, which separates these two groups, has the global vision test.

Test	Omission		Errors		Median times	
	t	p	t	p	t	p
Reaction time (central)	-0.601	0.549	-0.345	0.730	-5.284	< 0.001
Reaction time (peripheral)	-2.181	0.030	-1.083	0.280	-7.051	< 0.001
Multiple search	-2.157	0.032	-2.041	0.042	-3.147	0.002
Color discrimination	-4.995	< 0.001	-4.952	< 0.001	-3.459	0.001
Color-word interference	-4.636	< 0.001	-4.541	< 0.001	-1.998	0.047
Ground interference	-2.298	0.022	-3.055	0.002	-0.208	0.835
Divided attention (auditory)	-1.994	0.047	-2.706	0.007	2.915	0.004
Divided attention (visual)	-2.260	0.025	-0.603	0.547	-0.836	0.404
Digital span (direct)	-3.692	< 0.001	-2.192	0.029	-	-
Digital span (inverse)	-5.544	< 0.001	-0.465	0.642	-	-
Global vision (central)	-4.742	< 0.001	-	-	-7.688	< 0.001
Global vision (mid-peripheral)	-5.519	< 0.001	-	-	-5.360	< 0.001
Global vision (far-peripheral)	-5.399	< 0.001	-	-	-4.686	< 0.001

Tab. 3.1: t-test comparison of a set of attention test from [19].

In conclusion, this research [19] shows that assessment of attention can be simplified into several tests suitable for participants without any relevant experience in aviation. Computer-aided assessment can be a selective tool for most promising candidates or might be used with the integration of onboard instruments as a quick evaluator of current attention level. Another option is to deploy the system in an aviation school to develop more customized training programs.

3.4 Driver distraction detection

Driver distraction represents a similar issue as in general aviation. Most practical deployments [20] [21] dealing with inattention mitigation systems were in the field of the automotive industry. The most significant difference to the aviation sector is the diversity of sources of distraction and the higher prevalence of distraction events. These distractive tasks include eating, drinking, tuning the radio, using portables, and others. All these activities increase a cognitive load that may be dangerous.

A variety of methods could be used to detect inattention. However, non-intrusive detection sensors are preferred, such as an eye-tracking system or a single camera. The following research [21] proposes systems based on feature extraction using machine learning and image processing. These systems combine the detection of biomechanical, visual, and cognitive distractions, and they are able to extract multiple features with good performance only through a visual cue.

Biomechanical distraction

Biomechanical distractive factors, mentioned in literature [21], encompass all distractive activities involving hand action. The proposed approach uses computer vision-based machine learning methods to recognize predefined driving postures, such as operating the shift lever, grasping the steering wheel, eating, smoking, and holding a cell phone.

Visual Distraction

Visual distraction, according to the literature [22], belongs among the most common causes of traffic accidents. It is related to the use of mobile phones, navigation, and multimedia systems. The driver's response to these activities is characterized by the head rotation and eye gaze change away from the road. Visual distraction may cause occasional lapses, which could be potentially dangerous. These include imprecise control of the vehicle, missed events, and increasing reaction time. A lot of software-based distraction systems, mentioned in the literature [22], proposed a solution based on course information extracted from visual cues. They alert drivers in case of dangerous driving conditions, which occur by deflection from the forward gaze. Such a system can also work with head orientation composed of heading and pitch. Additionally, other software-based system [21] use combined information about head and eye orientation. This information is further processed by Distraction Calculation (DC) and Distraction Decision-Maker (DDM) algorithms, which estimate the driver's vigilance level. Following study [23] proposed several vision-based algorithm for evaluation of visual distraction:

- **Eyes off forward roadway** (EOFR), which estimates distraction by the cumulative off-road glances within the 6-second time window.
- **Risky Visual Scanning Pattern** (RVSP), which combines the evaluation based on cumulative off-road glances with the current glance estimation.
- **"AttenD"**, which estimates distraction based on glances to the forward, necessary glances for safe driving (such as at mirrors or speedometer), and not-related glances.

- **Multi distraction detection** (MDD), which estimates both visual and cognitive distraction, which is further clarified in the next paragraph. This algorithm improves the robustness of detection.

Cognitive distraction

Cognitive distraction covers a range of tasks, including conversation, listening, and spontaneously occurring processes like daydreaming or becoming lost in thought. The term of cognitive load is related to the driver's workload, which can be divided according to the literature [24] into the following groups:

- the primary task of driving a car
- secondary tasks (e.g., radio tuning)
- internal activities (e.g., mind-wandering)

Many indicators characterize secondary distracting tasks. Generally, distracting cognitive activity leads to a higher percentage of glances on the forward road. Moreover, drivers lose peripheral vision and perform narrower spatial scanning with fewer glances on mirrors and speedometer. Cognitive load causes a higher percentage of gaze towards the center of the road, specified by study [25] as the Percentage Road Center (PRC) parameter. A large cognitive load is indicated if PRC exceeds over 92 %.

Another valuable indicator of cognitive distraction, discussed in literature [21] is saccadic eye movements. Higher cognitive distraction is related to fewer saccades per unit time and a higher blink rate. Saccades are an important indicator of mental workload. Other suitable physiological features represent a pupil diameter. Its value increases with a cognitive load. Physiological measures useful for detecting cognitive distraction also include Heart Rate (HR), Heart Rate Variability (HRV), and skin conductance level. HR and skin conductance levels tend to increase as cognitive task load rises. These physiological measures can be measured concurrently by wearing physiological sensors or by an eye-tracking camera.

All these measurable cues can be evaluated based on machine-learning models compared in [21]. Following table 3.2 summarizes supervised learning algorithms used for cognitive distraction detection. In the following overview were different classifiers compared, such as AdaBoost algorithm, Extreme Learning Machine (ELM), Decision Tree, and Support Vector Machine (SVM). The proposed approaches use all previously mention features in various combinations. It reveals that the most relevant features are from an eye-tracking system followed by physiological characteristic as HR and pupil diameter. On the other hand, driving performance data was the least significant.

Features	Classifier	Accuracy
heart rate, eye gaze-related features, pupil diameter	AdaBoost	91.50%
eye gaze-related features, driving performance data	ELM	87.00%
eye gaze-related features, driving performance data	Decistion Tree	81.00%
eye gaze-related features	Decistion Tree	80.00%
eye gaze-related features, driving performance data	SVM	83.15%
eye gaze-related features	SVM	81.38%

Tab. 3.2: Comparative table of cognitive distraction detection methods. [21]

In conclusion, distraction is also influenced by several other factors from among mentioned above. For example, the influence of emotion and stress on the decision-making process. Many people also have different patterns of behavior depending on age and level of arousal. Therefore, the system needs to be tested as a simulation and then deployed in real situations. However, it follows from the literature [21] that it is appropriate to use commercial sensors such as eye-tracking systems because these systems offer competitive results. Exact results are important for applying data-driven detection mechanisms, especially machine-learning methods.

3.5 Discussion of proposed solutions

All of the methods reported in the state-of-the-art chapter covered the issue of inattention and suggested several detection and mitigation solutions. Introduced approaches were using two main ways to detect inattention. The first was a data-driven approach, which involves collecting large amounts of data from various sensors, training the machine learning model, and evaluating. The second approach presents the rule-based method, in which eye gaze data were evaluated using a set of conditions. This approach does not require such demanding data collection, but on the other hand, expert knowledge is needed. It regards mainly the connection between physiological characteristics and inattention. In particular, fixation duration, frequency of saccades, and scanning patterns belong to the most significant parameters.

The proposed sensors are preferred to be non-intrusive due to the better implementation in a real environment. It seems to be best to use an eye-tracking system, preferably a commercial one, due to better results. This solution can include a different number of cameras, from one up to eight. At the same time, the image from the cameras might be used to deploy computer vision methods to detect activities such as using portables. The cameras can perceive the highest possible number of cues in comparison to other sensors. These are the rotation and position of the head, gaze position, fixations, saccades, blink rate ant others. In addition, it is also reasonable to use other sensors to measure heart rate, skin conductance, and brain waves from physiological values. However, these data are not as determining inattention as they are rather indicative about a level of cognitive load that may cause inattention.

Among the proposed implementations in state-of-the-art review belong:

- an inattention monitoring system for general aviation pilots
- pre-flight inattention testing system
- a design of customized training programs
- assessment of pilot candidates

4 Machine Learning

Machine learning (ML) is an area of computer science that gives computers the ability to learn without being explicitly programmed [26]. It collects methods that automate building data-driven models through a systematic discovery of statistically significant patterns in the available data. ML has the capability to improve the performance of tasks through exposure to data and experience. Firstly, the ML model learns from the data it is exposed to and then applies the knowledge to predict another set of data. Machine learning algorithms, according to the nature of the data, are divided into the following categories, as reported to the literature [27]:

- supervised learning
- unsupervised learning
- reinforcement learning

Supervised learning is the category of ML, where algorithms observe training data together with labeled output. This output indicates an example of whether data has a specific property. The ML task is to generalize from given inputs to the new, previously unseen examples [28]. An example is an e-mail filter that allows classifying incoming e-mails to the various folders (e.g., spam, work, personal) . This also applies for an example of the binary classifier of the state of inattention and distraction.

Unsupervised learning indicates a method where the algorithm is exposed to data, which applies in the future to provide a prediction. The ability to search and discover hidden patterns are particularly beneficial. Unsupervised learning methods can be used as predictive modeling or as a help to perform decision-making tasks under uncertainty. For example, unsupervised ML methods are applied to the internet services to learn individual user patterns to seek their preference. This technique allows the creation of various robots, which learn new skills and adapt to the environment. [29]

Reinforcement learning outlines an algorithm that interacts with a dynamic environment—for example, flying an aircraft or playing a game against an opponent. The algorithm works on the principle to take actions in an environment, as the program provided feedback to maximize the results. [27]

4.1 Supervised learning

Supervised learning builds a model that makes predictions based on evidence in the presence of uncertainty. This kind of ML task learns a function that maps an input to an output based on examples of input-output pairs. In the general scenario, the training set consist of n ordered pairs $(x_1, y_1), (x_2, y_2), (x_i, y_i)$, where each x_i is some measurement or the feature vector of the i-th example and y_i is its label for that data point. It is assumed that the training set consists of independent and identically distributed pairs. An example of x_i might be a group of (or a vector) of measurements. The corresponding y_i is then a classification of the state (e.g., distraction or attention), as reported in literature [30].

Moreover, a training set is used to find a deterministic function that maps any input to output, predicting future input-output observations while minimizing errors as much as possible. Then, the output of the learning algorithm is a function $f : X \Rightarrow Y$, called a hypothesis, that aims at predicting $y \in Y$ for arbitrary $x \in X$, preferably for those that are not contained in training data. The goal of the learning algorithm is to find a good hypothesis f. In order to measure how a function fits the training data, a loss function $L : Y \times Y \Rightarrow R$ is defined. Depending on whether Y is continuous or discrete one, it is distinguished between two types of learning problem:

- classification
- regression

Classification techniques predict discrete response Y, in which a function from X to Y is also called a classifier. The classification task is used for data, which can be tagged or categorized into specific groups of classes (e.g., attention, distraction) [32]. Common algorithms for performing classification include support vector machine (SVM), boosted and bagged decision trees, k-nearest neighbor, Naive Bayes, discriminant analysis, logistic regression, and neural networks [33].

Regression methods predict continuous responses. Typical applications include electricity load forecasting or algorithmic trading. Common regression algorithms represent linear model, nonlinear model, regularization, stepwise regression, boosted and bagged decision trees, neural networks, and adaptive neuro-fuzzy learning. [33]

4.2 Decision Trees

The decision tree is one of the ML predictive methods that use a flowchart-like tree structure to illustrate relationships between input predictors from the dataset and the output classes. The target variable of a decision tree might be either discrete or continuous. Tree models with a discrete set of output values are classification trees. In these structures, the output variable is a discrete value representing conjunctions of features that lead to the class label. Another type of decision tree is the regression trees with continuous output values. In general, a decision tree can be visualized to present decisions and the process of decision-making explicitly. Regardless, the use of single decision trees is too simplistic. Furthermore, classification and regression trees are used in ensemble methods constructing more than one decision tree. [34]

4.3 Ensemble learning

Ensemble methods are composed of multiple classifiers that improve their performance against single decision tree algorithms. The aim is to increase accuracy by combining responses from multiple classifiers (often called “weak learners”) into a single response. In general, ensemble learning tends to yield better results because they seek diversity among the models they combine. [35] In order to set up an ensemble learning method, the base models have to be aggregated. In general, an ensemble learning system is homogenous because they are composed of classifiers trained with the same learning algorithm. Contrary, heterogeneous methods consist of classifiers trained with different learning algorithms. The choice of weak learners is an important task that should be coherent with model aggregation. According to literature [36], there are these significant kinds of meta-algorithms that aim at combining weak learners:

- bagging
- boosting
- stacking

Bagging considers homogenous weak learners that learn independently from each other in parallel and combines them in a deterministic averaging process. Boosting methods offer homogeneous weak learners that learn sequentially in an adaptive way and combines them in a deterministic strategy. The last approach is stacking, which considers heterogeneous weak learners in parallel and combines them by training a meta-model to create a prediction based on the different weak model’s predictions.

4.4 Boosting

Boosting is the approach that produces an ensemble model working similarly to a bagging method. The model is aggregated to obtain a strong learner. Boosting is a technique that consists of fitting sequentially multiple weak learners in an adaptive way. Each model in the sequence is fitted, giving more importance to observations in the previous model's data in the sequence. Each following model focuses its efforts on the most challenging observations. In the end, a strong learner with lower bias is obtained. Boosting methods are used for both regression and classification problems. Boosting itself is primarily focused on reducing bias. [36]

The boosting algorithms differentiate between each other in their method of weighting training data points and hypotheses [37]. Among the most popular belongs AdaBoost, LogitBoost, LPBBoost, and RUSBoost.

4.5 RUSBoost

RUSBoost is a random undersample boosting algorithm helping to balance the class distribution of data. The problem of class imbalance is common in many application domains. It is possible to alleviate the class imbalance with data sampling or boosting. RUSBoost uses both methods as a hybrid algorithm. Data sampling balance the class distribution in training set by oversampling or undersampling. RUS refers to the random undersampling method that removes examples randomly from the majority class until the desired balance is achieved. The benefit is the saved time required for training a classifier. The second technique of RUSBoost algorithm to improve classification tasks is boosting. RUSBoost used the combination with AdaBoost that iteratively build an ensemble of models. During this process, the weights are modified to classify examples in the next iteration correctly. After completion, all constructed models participate in a weighted vote to classify unlabeled data. [38]

Algorithm RUSBoost

The RUSBoost algorithm is further discussed in detail with reference to the literature [39]: Let x_i be a point in the feature space X and y_i refers to class label from Y. Each of m example can be represented as a tuple (x_i, y_i). Let t be an iteration between one and the maximum of iterations T that presents a number of classifiers in the ensemble. h_t refers to the weak hypothesis trained on iteration t and $h_t(x_i)$ is the output of hypothesis h_t. Let D_i be the weights of the ith example on iteration t. In the first step, the weights are initialized to $\frac{1}{m}$, where m is the numbers of samples in the training data. In the following steps T weak hypotheses are iteratively trained. Let us assume that given are:

- set S of examples $(x_1, y_1), ..., (x_m, y_m)$ with minority class $y^r \in Y, |Y| = 2$
- weak learner W
- number of iterations T
- desired percentage of instances to be represented by the minority class N

In the first step, the samples are randomly undersampled to aim $N\%$ of the new training data set $S_t^{'}$ belongs to the minority class. In the next step, $S_t^{'}$ and $D_t^{'}$ are passed to the base learner W, which creates the weak hypothesis h_t. In equation 4.1 is calculated pseudoloss ϵ_t and in equation 4.2 the weight update parameter α. The weight distribution for the next iteration D_{t+1} is updated and normalized. Step 2 is performed in T iterations until the final hypothesis $H(x)$ is returned as a weighted vote of the T weak hypotheses in equation 4.5.

1. initialize $D_1(i) = \frac{1}{m}$
2. iterate through each entry $t = 1, 2, ..., T$
   (a) create temporary training dataset $S_t^{'}$ with distribution $D_t^{'}$ using RUS
   (b) call W providing it with samples $S_t^{'}$ and wights $D_t^{'}$
   (c) get a hypothesis $h_t : X \times Y \Rightarrow [0, 1]$
   (d) calculate the pseudo-loss for S and D_t:
$$\epsilon_t = \sum_{(i,y):y_i \neq y} D_t(i)(1 - h_t(x_i, y_i) + h_t(x_i, y)) \tag{4.1}$$
   (e) calculate the weight update parameter:
$$\alpha_t = \frac{\epsilon_t}{1 - \epsilon_t} \tag{4.2}$$
   (f) update D_t:
$$D_{t+1}(i) = D_t(i)\alpha_t^{\frac{1}{2}(1+h_t(x_i,y_i)-h_t(x_i,y:y\neq y_i))} \tag{4.3}$$
   (g) normalize $D_t + 1$:
$$D_{t+1}(i) = \frac{D_{t+1}(i)}{Z_t} \tag{4.4}$$
3. output the final hypothesis:
$$H(x) = \underset{y \in Y}{\operatorname{argmax}} \sum_{t=1}^{T} h_t(x, y) \log \frac{1}{\alpha_t} \tag{4.5}$$

The study [39] deals with performance measurement of boosting algorithm, which was compared with empirically related classification models as AdaBoost and SMOTEboost with RUSBoost. The test was performed on several datasets from various application domains, e.g., CCCS12, SP3, PCI, SatImage, Ecoli4, and SolarFlare F. The performance of RUSBoost across all tested datasets occurs as significantly better than other classification models, and it has been shown to result in excellent performance for imbalanced training data model while reducing computational complexity and training time.

4.6 Validation procedures

Model validation provides an evaluation of a trained model on test data set. It supports the estimation of a model skill while tuning the hyperparameters. If the data set is large enough, there is no need for validation techniques. The primary method of validation is the data split into train, validation, and test data. A typical ratio for this metric might be 8:1:1. After training the ML model, the process will move onto validation and tuning the hyperparameters with the validation data set till the model reaches a satisfactory performance metric. Similarly, the testing process can be performed on a separate data set. [40]

In typical scenarios, the data are not always representative enough. Then it is necessary to use some of the validation techniques, as the literature [40] suggests:

- k-fold cross-validation
- leave-one-out cross-validation (LOOCV)
- random undersampling
- bootstrapping

k-fold cross-validation

In the technique shown in fig. 4.1, the dataset is split into k number of folds, where one fold is used as a validation set and the rest is used as the training data set. This process is repeated in n number of times as specified by the algorithm. The advantage is that the entire data is used for training and validation. The error rate is the average of the error rate of each iteration.

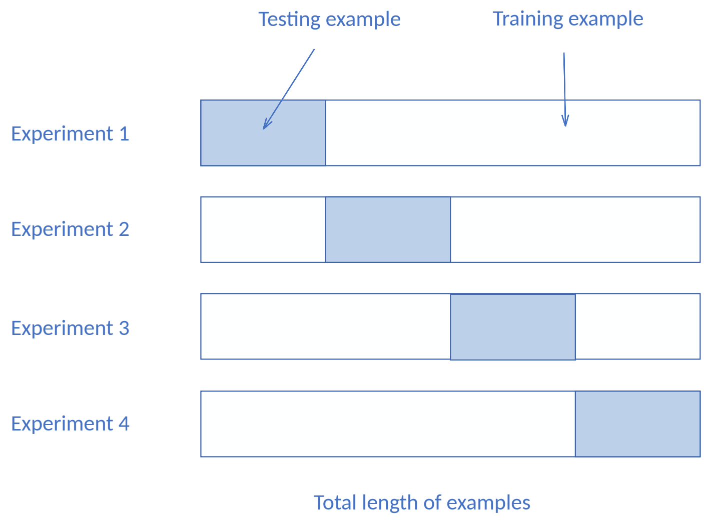

Fig. 4.1: k-fold cross-validation scheme.

Leave-one-out cross-validation (LOOCV)

All of the data except one record is used for training, and one record is used for validation, as shown in fig. 4.2. This is iteratively repeated for N times (N is a number of records). The advantage is similar to the $k$fold cross-validation. Whole data are used for training and validation. The error rate of the model is the average error rate of each iteration.

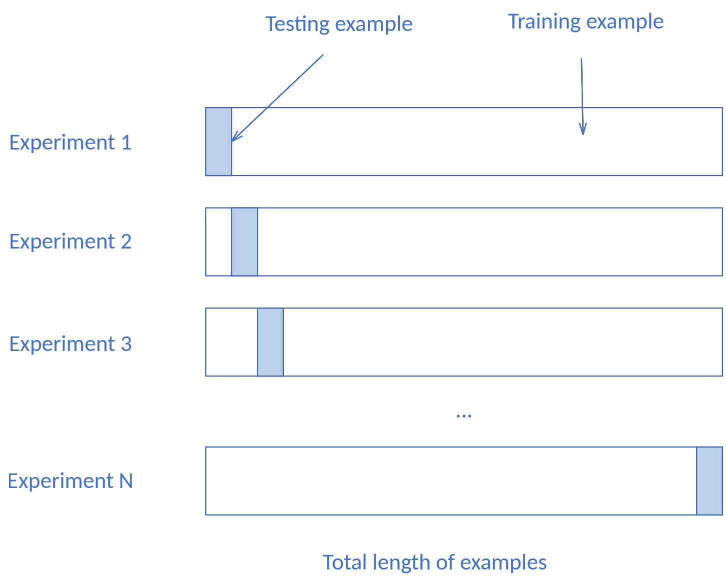

Fig. 4.2: Leave-one-out cross-validation (LOOCV).

Random Subsampling

Multiple data sections are randomly chosen from the dataset and combined to form a validation dataset. The remaining sections form the training data set, as illustrated in fig. 4.3. The error rate of the model is the average error rate of each iteration.

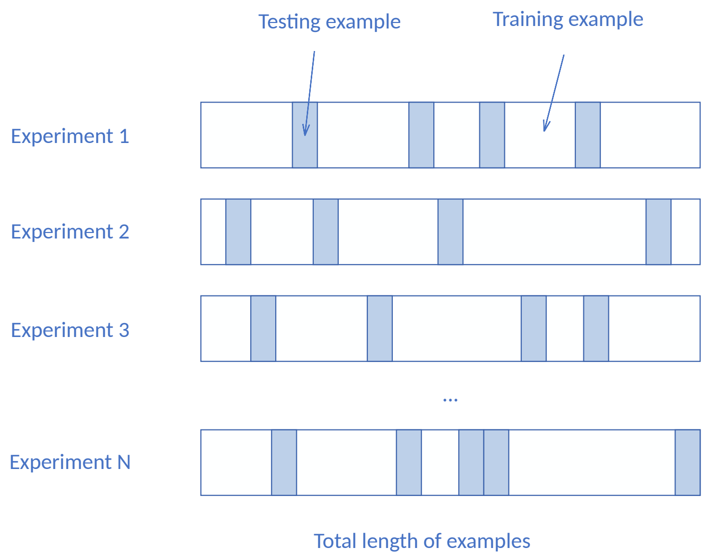

Fig. 4.3: Random Subsampling.

4.7 Performance metrics

In order to quantify the quality of the machine learning model, different performance metrics are computed. Evaluation of ML algorithm is an essential part of finding out if the model satisfies the results as expected. Among the essential metrics belong confusion matrix, accuracy, precision, sensitivity, specificity, and F_1 score [41].

Confusion Matrix

The confusion matrix is often used to describe the performance of the ML classification model. As shown in fig. 4.4, it is a type of contingency table with two dimensions: actual and predicted and sets of labels in both dimensions. During testing the model, four possible outcomes can occur: True Positive (TP), True Negatives (TN), False Positives (FP), False Negatives (FN). [42]

		Predicted Class	
		Positive	Negative
Actual Class	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

Fig. 4.4: Confusion matrix.

Accuracy

Accuracy is the ratio of the number of correct predictions to the total number of input samples.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4.6}$$

Precision

Precision is the amount of positives recognized from the total amount of predicted positives.

$$Precision = \frac{TP}{TP + FP} \tag{4.7}$$

Sensitivity

Sensitivity (True Positive Rate) measures the amount of positives recognized from the total amount of positives.

$$Sensitivity = \frac{TP}{TP + FN} \tag{4.8}$$

Specificity

Specificity (True Negative Rate) refers to the amount of negatives recognized from the total amount of negatives.

$$Specificity = \frac{TN}{TN + FP} \tag{4.9}$$

F_1 score

F_1 score is the harmonic mean between precision and recall:

$$F_1 = \frac{2 \times TP}{2 \times TP + FN + FP} \tag{4.10}$$

Receiver Operating Characteristics (ROC)

In machine learning, the Receiver Operator Characteristic (ROC) is an evaluation metrics for binary classification problems. It is a curve that plots the True Positive Rate (TPR) against False Positive Rate (FPR) at various threshold values. Area Under Curve (AUC) is equal to the probability that the classifier will rank a randomly chosen positive example higher than a randomly chosen negative example. This metric describes the ability of the classifier to distinguish between classes [43]. False Positive Rate and True Positive Rate are ranging between zero and one. FPR and TPR are computed at a varying threshold, as shown in fig. 4.5.

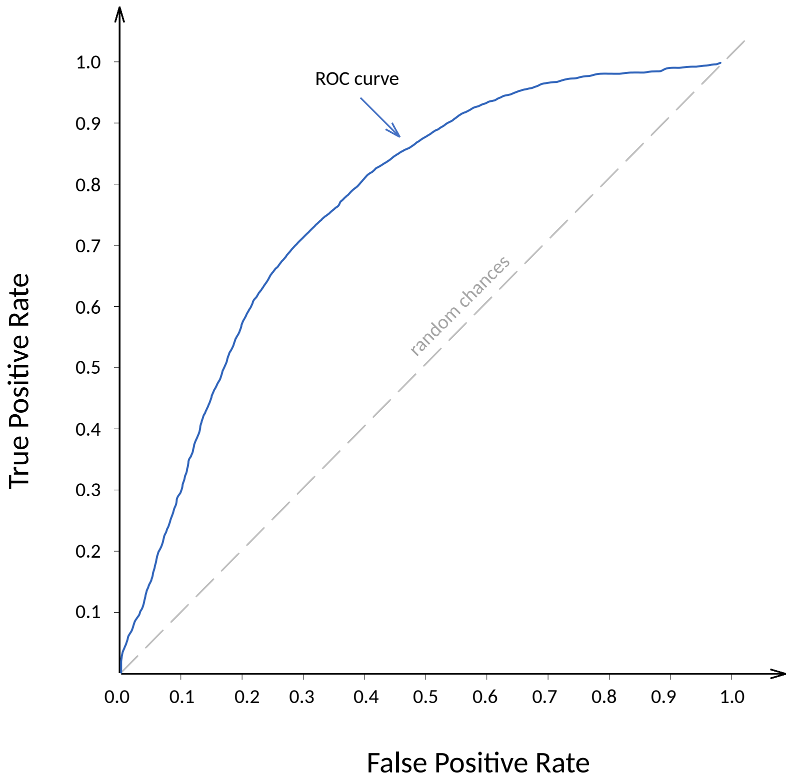

Fig. 4.5: Receiver operating characteristics (ROC) curve and Area Under the Curve (AUC) compared with the random chance curve. Inspired by [43].

5 Expert systems and machine reasoning

The term of expert systems represents a knowledge-based system from an area of artificial intelligence (AI). Expert systems are specifically intended to model human expertise or knowledge. These can be either factual or heuristic knowledge that concerns some specific area. The expert system is able to produce inferences to solve a given problem. These problems are generally difficult enough to require human expertise for a solution. Hence, the expert system emulates the decision-making of human experts. A typical expert system involves a fact database, knowledge base, an inference engine, as shown in fig. 5.1. [44]

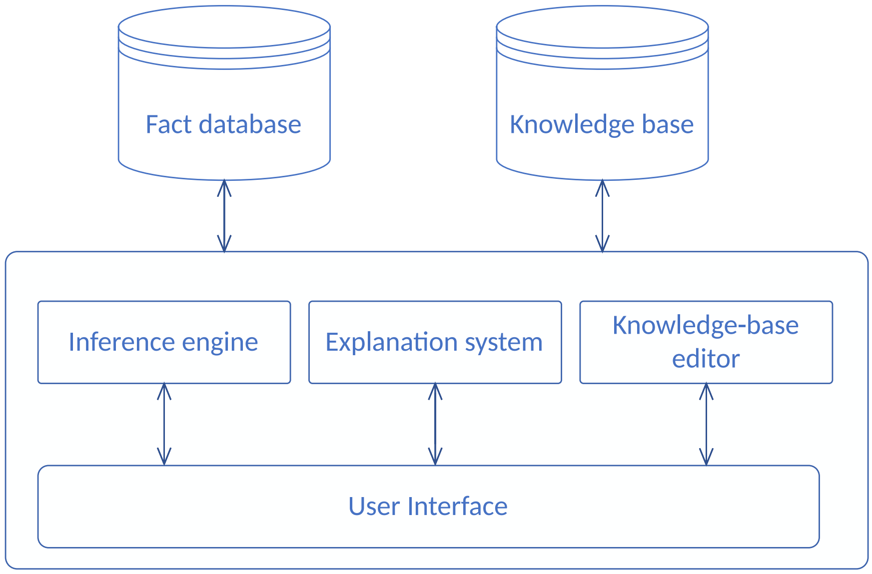

Fig. 5.1: Expert system architecture.

The fact database contains statements that refer to some specific domain. These are the case-specific data. The knowledge base is the domain where knowledge is expressed in the form of a series of rules (e.g., if a pilot is speaking or looking right). The explanation system provides information on how the inference engine arrived at its conclusions. It is an essential part of every expert system. If the system is faulty reasoning, then the user can understand the data examined by the explanation system. The inference engine derives conclusions from rules and facts that user specified. It uses either forward chaining, backward chaining, or a combination to make inferences from available data. The knowledge-base editor allows the user to edit the information in the knowledge base. These features contribute greatly to the power and ability of an expert system, which distinguish the expert system from a traditional programming language. The main advantage of every expert system presents scalability and flexibility. A large amount of knowledge can be systematically divided into rules and facts. These can be easily modified, added, or removed. [45]

Inference engine, explanation system, and knowledge-base editor are the parts of every expert system. These system parts are combined into the expert system shell. It is a general tool that might be used for building various expert systems. Examples of such shells are CLIPS, OPS5, ART, JESS, and Eclipse.

5.1 CLIPS

CLIPS (an acronym for C Language Integrated Production System) is an expert system developed by the Software Technology Branch of NASA in the 80s of the 20th century. It is an expert system shell, which is easily accessible public software. The advantage of CLIPS is the integration with other procedural languages such as C, Python, and Java. It allows to execute a CLIPS fraction by another procedural language facilitating the development of rule-based systems. With reference to the documentation [45], CLIPS provides the three fundamental elements of every expert system:

- fact list
- knowledge base
- inference engine

Fact list provide a global memory for data, which contains facts. Knowledge base includes all defined rules and inference engine performes inferences or reasoning.

5.2 Facts and rules

CLIPS expert system [47] relies on the input information, which is represented as a set of rules and facts. They are formed according to expert knowledge from a specific area. In general, facts are statements that are related to some true affirmation. In this thesis, the facts are derived from sensors using parametrization. In CLIPS, facts are stored by asserting them into the fact database using `assert` command, as shown in listing 5.1.

Listing 5.1: Example of fact statements

```
CLIPS> (assert (heading-right))
<Fact-1>
CLIPS> (assert (speaking))
<Fact-2>
CLIPS> (assert (hand-up))
<Fact-3>
CLIPS> (facts)
f-1 (heading-right)
f-2 (speaking)
f-3 (hand-up)
For a total of 3 facts.
CLIPS>
```

Facts are placed into the fact database, where each asserted fact have their fact number. Facts may also be retracted from the fact database using the `retract` function. However, the application of rules is important to develop a capable expert system. Each rule is expressed in the form of “IF ... THEN ...” statement. The expression differs from traditional procedural language. In CLIPS, a rule statement looks as shown in the following listing 5.2.

Listing 5.2: Example of rule statement

```
(defrule conversation
  (pilot-speaking)
  (heading-right)
  =>
  (assert (pilot-conversation)))
```

A rule consists of the left-hand side (LHS) and the right-hand side (RHS) divided by the row sign. The part of LHS consists of a unique name and defined pattern (”IF” part) of the rule. RHS presents an action (”THEN” part).

In plain language, the above listing 5.2 means: ” IF a pilot is speaking and his/her heading is right, THEN it means pilot conversation.” An expert system makes inferences from data, which results from one rule and can be used as the pattern for another. It is the power of rule-based programming. When the agenda activates multiple rules, CLIPS allows to order the activation by increasing priority or salience. Patterns in the rule are automatically connected with logical conjunction, which means that both facts must be true to assert the action. CLIPS also has build-in functions to test conditional elements, including logical, arithmetic, and comparison functions.

6 Data collection platform

As a first step, a data collection platform was designed. It includes the selection of suitable sensors based on the knowledge and outcomes from the literature review. As a non-intrusive sensor, an eye-tracking system using two cameras was chosen. Other sensors were mildly intrusive, such as the wristband for measuring hand movements. It was also decided to use an inertial sensor as an alternative sensor to the eye-tracking system. This sensor measures the rotation and inclination of the head, and it is located on the headphones. In addition, the pilot's voice from the headphones and sound in the cockpit were recorded. Data from all sensors were concentrated into a data collection platform, shown in fig. 6.1.

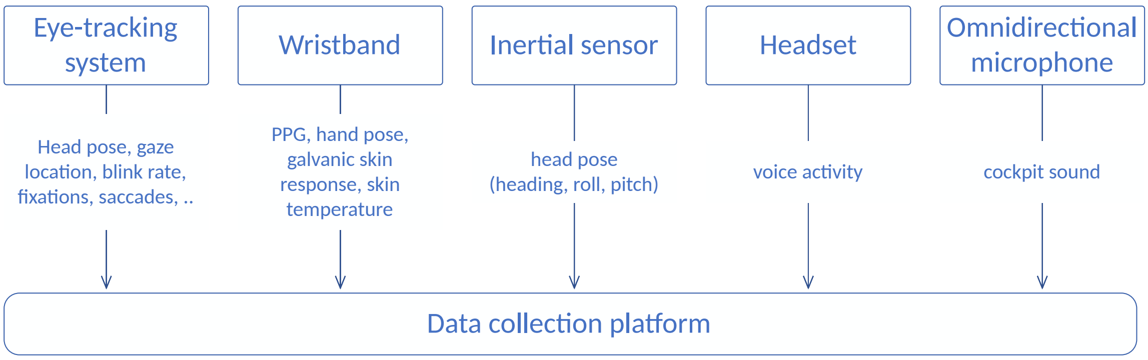

Fig. 6.1: Block scheme of data collection platform with used sensors.

6.1 Eye-tracking system

In general, the eye-tracking system used for the data collection consists of multiple visual cameras and an image processing unit, as shown in fig. 6.2. The system works with monochrome cameras. The number of cameras depends on the desired field of view. In the following measurements, two cameras are used to ensure appropriate coverage. The vision system also uses illuminators which provides sufficient lighting conditions even in a dark environment. Before use, it is necessary to perform calibration and adjust the exposure. A multiplexer further processes data from each camera into one stream. This data stream is fed to a computing unit through a USB interface. The selected eye-tracking system presents a commercial product as a comprehensive software solution providing accurate and competitive measurements. The computer unit provides an evaluation of several cues, including:

- head position
- head heading, pitch and roll
- gaze heading and pitch
- eye position
- eye fixation, blinks and saccades
- pupil diameter

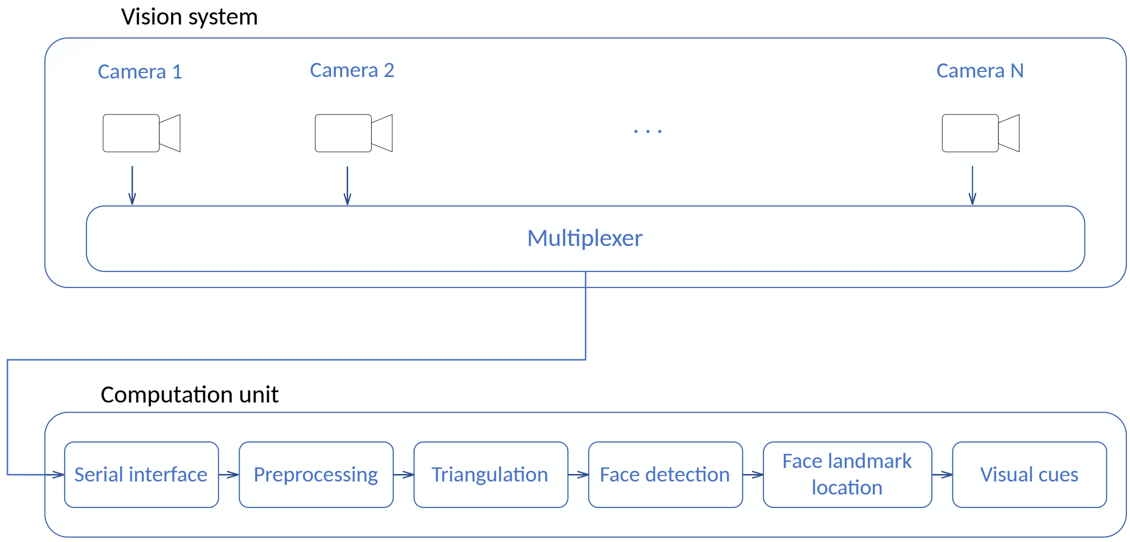

Fig. 6.2: Schema of eye tracking system.

Following table 6.1 describes the parameters of the cameras used for the eye-tracking system.

Dimensions	3x3x3 cm
Interface	Universal Serial Bus 3 (USB 3.0)
Sampling rate	60 Hz
Resolution	2 Megapixels
Field of view	90° - 360° (depending on mumber of cameras and the lens used)
Head box	For a typical 2-camera screen measurement set-up (freedom of head movement) 8 mm lenses: 40x40x50 mm. Adjustable with lenses and positioning of cameras.
Eye distance	30 - 300 cm - adjustable with lenses and positioning of cameras.

Tab. 6.1: Eye tracking camera parameters.

6.2 Inertial sensor

The inertial sensor was chosen as a potential low-cost replacement to the eye-tracking system. It allows the measurement of head heading, pitch, and roll analogically to the eye-tracking system. This type of sensor contains a combination of an accelerometer, a gyroscope, and a magnetometer. The individual chips differ in technical details such as sampling frequency, ranges, data outputs, and presence of the additional computation unit. The quality of the sensor also occurred as a common problem. The following sensors were compared:

- MPU9255
- BNO055
- LSM9D1

All mentioned multichip contains a 3-axis gyroscope, accelerometer, and magnetometer with detailed scales and bit ranges described in datasheets [49] [50] [51]. Compared to the others, BNO055 presents a "system in package", illustrated in fig. 6.3, providing output as fused data from sensor computation unit.

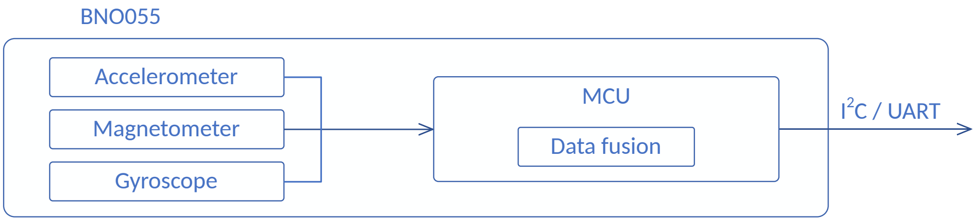

Fig. 6.3: Block diagram of BNO055 chip from datasheet [49].

Sensors MPU9255 and LSM9D1 require the implementation of converting function from accelerometer and magnetometer values to angles. These implementations are often simplistic and inaccurate. The advantage of the BNO055 chip is a fusion unit that calculates Eurel angles and thus indicates heading, pitch, and roll describes in tab. 6.2.

Rotation angle	Range
Pitch	+180° to - 180°
Roll	-90° to +90°
Heading	0° to +360°

Tab. 6.2: BNO055 rotation angle conventions. [50]

The inertial sensor was connected over the I^{2}C interface with Arduino Uno, shown in fig. 6.4. This arrangement was implemented to secure a connection between the sensor and the data collection platform.

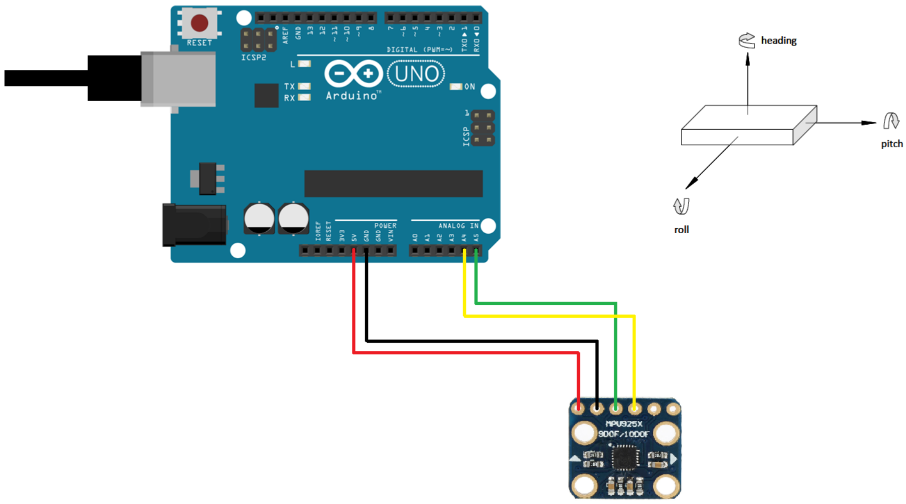

Fig. 6.4: Wiring diagram of multi-chip module MPU-9255X with Arduino Uno (left). Orientation of axes and polarity of rotation (right).

6.3 Wristband

The wristband presents a wearable that includes a measuring unit of a wide range of cues, summarized in tab. 6.3. It involves multiple sensors placed close to the surface of the human skin. Measured modalities provide a photoplethysmogram (PPG), 3-axis accelerometer, electrodermal activity (EDA) sensor, and infrared thermopile to obtain skin temperature. In this work, only the data from the accelerometer are used.

Measured modalities	
PPG	Sampling frequency: 64 Hz Returned cue: Inter-beat interval
Acceleration	Sampling frequency: 32 Hz
Skin temperature	Sampling frequency: 4Hz
Galvanic skin response	Sampling frequency: 4Hz

Tab. 6.3: Wristband parameters

6.4 Audio channel

The data collection platform also includes two microphones to record the voice activity of the pilot and the sound in the cockpit. The first microphone is a part of the headset, which the pilot usually uses during the flight. This microphone captures only the voice of the pilot using noise cancellation. The second microphone is located in the cockpit. This device is based on an omnidirectional microphone, which allows recording the overall sound in the cockpit, including the voice of the co-pilot, flight attendant, passenger, and various warning signals.

7 Data collection

This chapter describes the process of data collection. It involves the practical use of all sensors mentioned in the previous chapter. Data collection took place in the static simulator of the Airbus A320, shown in fig. 7.1. The data collection was using the pre-prepared scripted scenario simulating pilot behavior. Each participant sat on the captain seat, wore a wristband and headphones with an inertial sensor. The cameras were located on the dashboard. One of them captured the face in the straight direction and the other one slightly from the right side.

Fig. 7.1: Static simulator of an Airbus A320 aircraft during a data collection.

In a nutshell, experimental measurement took approximately 12 minutes and included either attention and distraction activities in separate blocks. Informations about each session is summarized in tab. 7.1.

Session number	Session length	Attention block	Distraction block	Wristband position	Number of cameras
1	707 s	298 s	409 s	right	2
2	709 s	260 s	449 s	right	2
3	662 s	328 s	334 s	right	2
4	848 s	371 s	477 s	right	2
5	907 s	405 s	502 s	left	2

Tab. 7.1: General overview of measured sessions.

7.1 Data collection protocol

The prescribed scenario was prepared with a human factors specialist. The scenario represents significant manifestations of the state of attention and distraction. This protocol is used for participants with minimal or no aviation knowledge to simulate pilot proper and improper behavior.

Attention

The state of attention describes activities related to piloting an aircraft. Technically, the pilot has situation awareness and full control over the aircraft. The pilot performs activities related to the flight, such as responding to ATC commands. Simultaneously, the pilot may lead a short dialogue without an attention leak. The following instructions, in fig. 7.2, describe general outline for attention activities:

- Scan each flight instrument, overhead panel.
- Look at the central control panel (throttle, keyboard, FMS).
- Follow and respond to the ATC instruction.
- Set the autopilot using the knobs and buttons.
- Look and hold the joystick.
- Look straight out of the cockpit and at the Primary Flight Display (PFD).
- Look for traffic out of the window.
- Have a short conversation with the co-pilot or the flight attendant.

Distraction

Distraction is a condition in which pilots lose attention and consequently also a situation awareness. Pilots can be distracted by several factors, such as visual, auditory, and cognitive. These are represented by using portables or by a conversation with the crew member. During all these activities, the pilot stops monitoring the flight instruments. The general timeline of distraction activities is shown in fig. 7.3. The individual instructions are described as follows:

- Look straight ahead and fix the view (dreamy, mind-wandering).
- Take a look out of the cockpit.
- Look off the aviation-related instruments.
- Read from a smartphone.
- Look at the co-pilot and have a conversation.
- Look at the flight attendant and have a conversation.
- Read from the map or a flight manual.

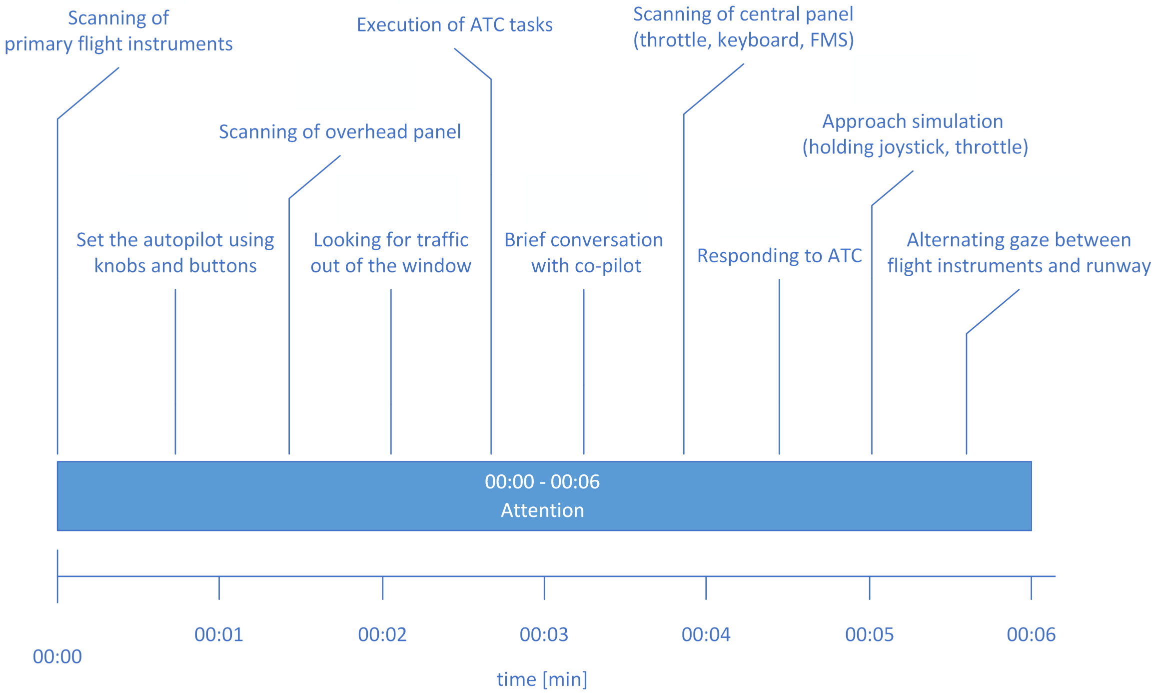

Fig. 7.2: General timeline of attention activities block.

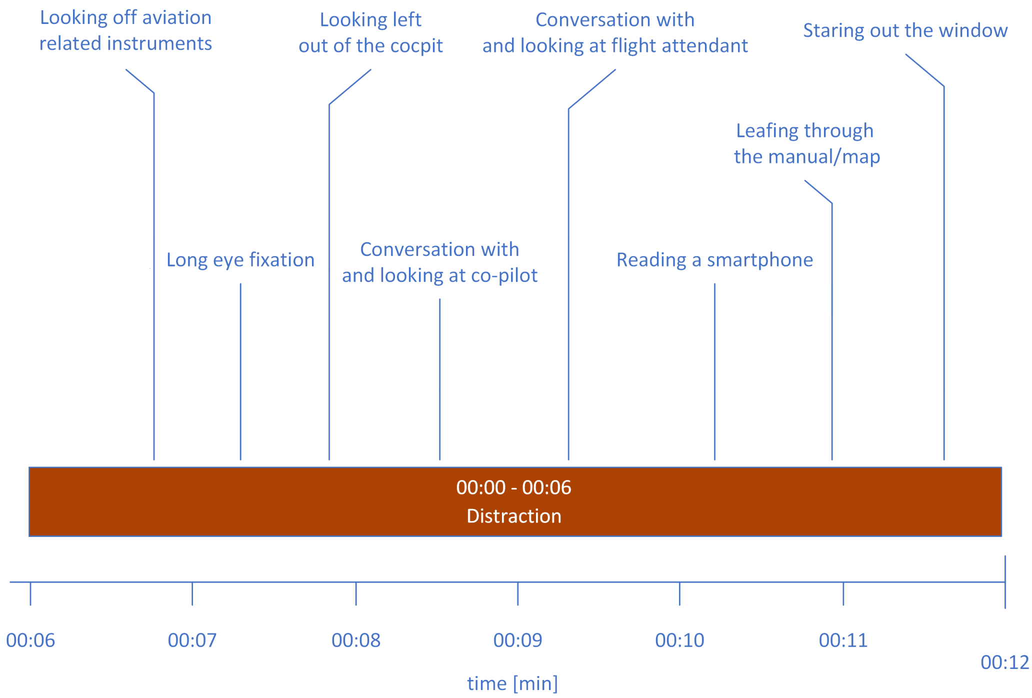

Fig. 7.3: General timeline of distraction activities block.

7.2 Data analysis

This section covers the analysis of measured signals. Fig. 7.4 shows signals of the head movement from the inertial sensor, eye-tracking system, and wristband compared together. The figure also shows two audio channels, which are rather informative. According to the previous scheme in fig. 7.2 and fig. 7.3, the sessions were divided into two parts, including two types of activity blocks. The following figure shows the selected signals from the sensors in a randomly selected session. The headset inertial sensor and eye-tracking head signals did not include the roll value, which is considered as insignificant for inattention detection. The disadvantage of eye-tracking signals is the discontinuity that occurs in the output data, which is caused by poor quality. This phenomenon appears in the case when the position of a pilot head is out of the field of view. On the other hand, the signals from the inertial sensor are not degraded by quality changes but by sensor inaccuracies, which are significant in the case of MPU9255 chip.

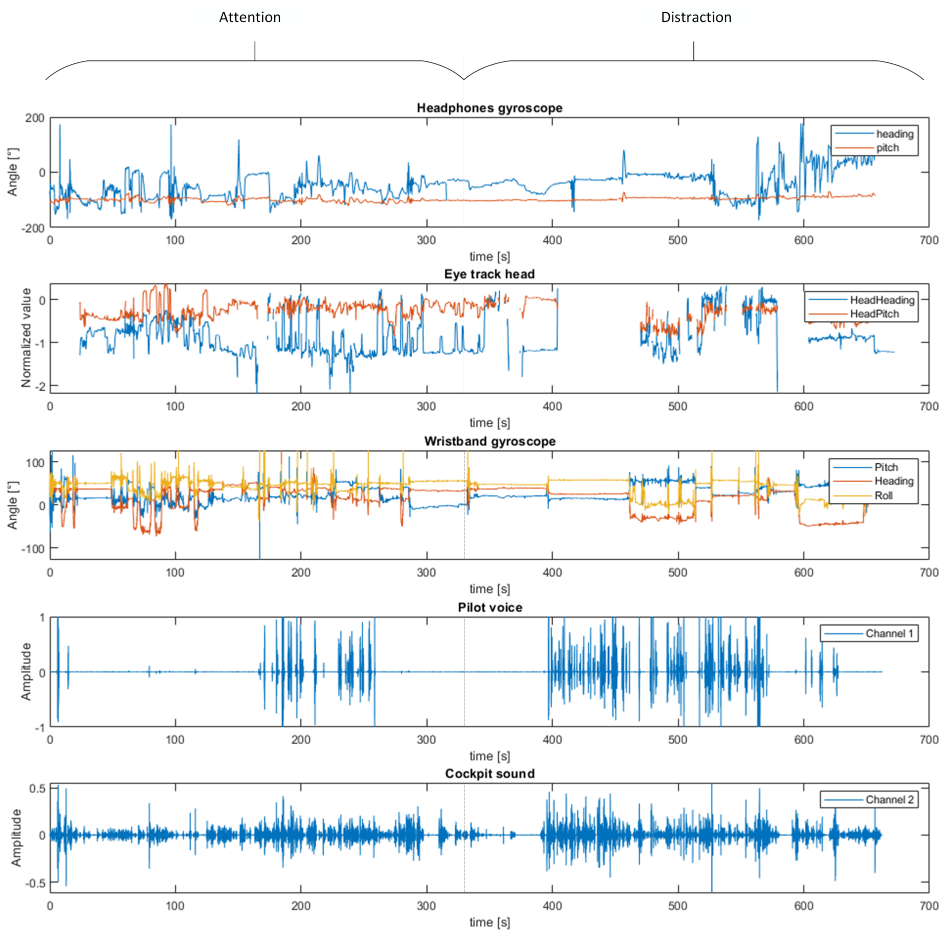

Fig. 7.4: Annotation of the session no. 3.

Attention

The zoom of the attention session block, in fig. 7.5, shows the influence of individual flight-related activities on the measured signals. Heading and pitch signal deviations may be noticed in a situation as setting the autopilot or holding the joystick. The signal represents an attention state, mainly due to the typical pilot's scanning technique.

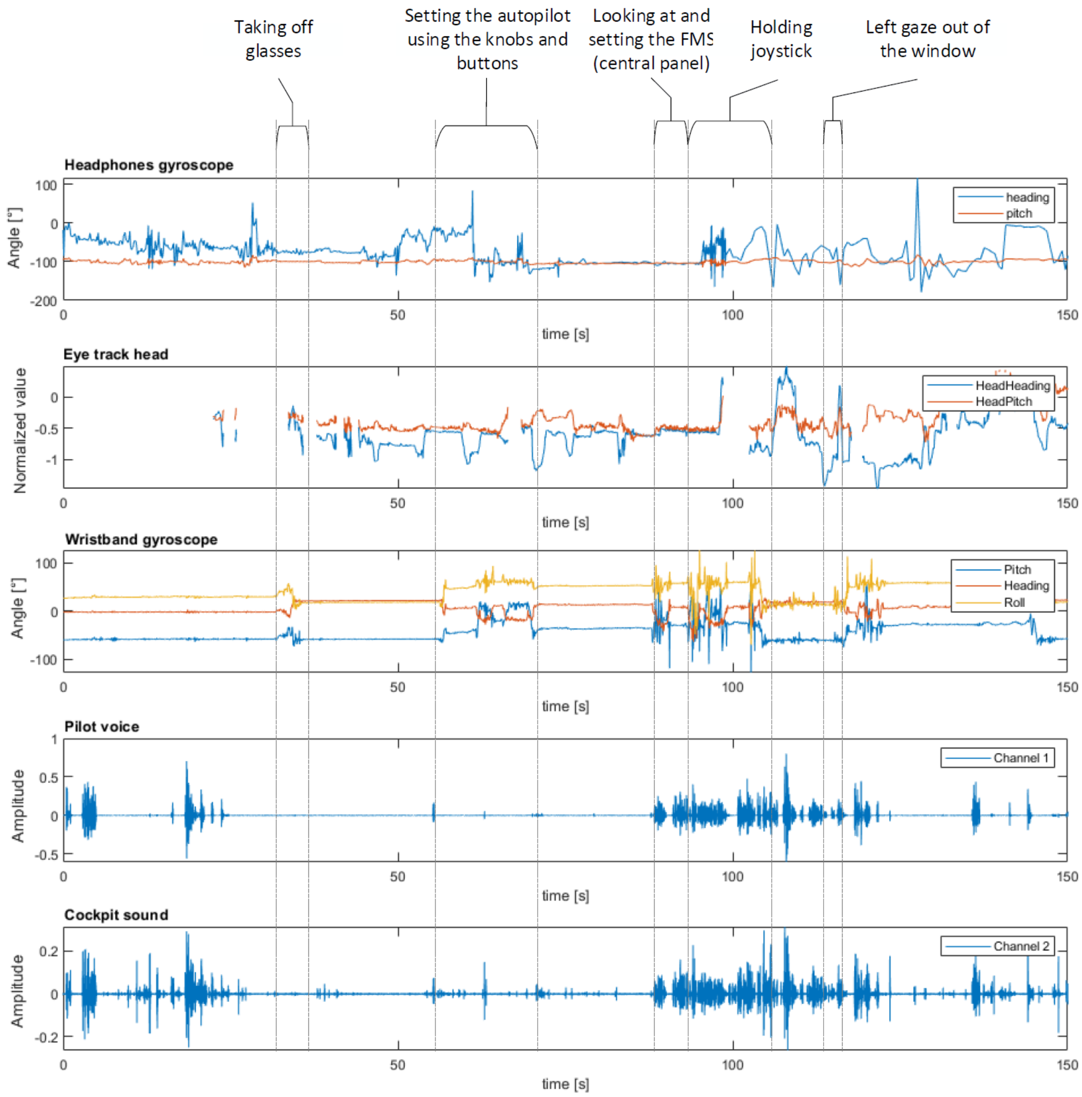

Fig. 7.5: Annotation of zoomed selection of attention session.

Distraction

The zoom of the distraction session block, in fig. 7.6, shows the influence of individual distractive activities. All sensors did not detect all activities. However, the sensors can complement each other in different activities, as reading or browsing through a magazine. In these signals can be found the absence of scanning of aviation instruments. The signals from the eye-tracking system vary due to insufficient quality and indicate that the head position is out of the field of view.

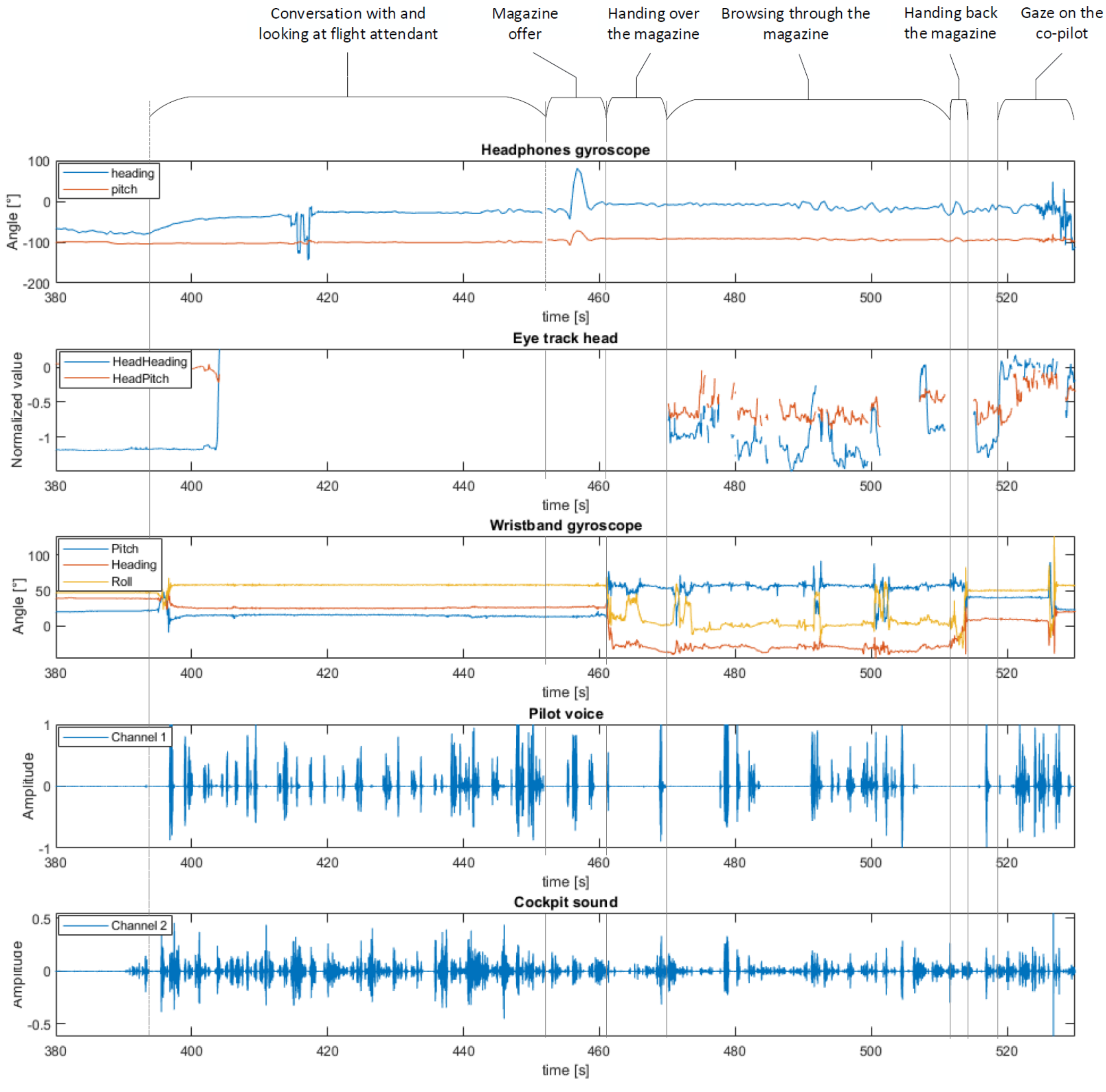

Fig. 7.6: Annotation of zoomed selection of distraction session.

8 Classification experiment

8.1 Feature extraction

The first step was to select cues from sensors and extract appropriate features from them. Tab. 8.1 shows the selected cues from the individual sensors. These cues contain information about head and hand position and orientation. The eye-tracking system additionally includes data about gaze orientation, eyelid opening, saccades, and fixation.

Sensor	Cues
Eye tracking system	Head position (x, y, z axis), Head orientation (heading, pitch, roll), Gaze orientation (heading, pitch, roll), Eyelid opening, Saccades, Fixation
Inertial sensor	Head orientation (heading, pitch, roll)
Wristband	Hand movements (heading, pitch, roll)

Tab. 8.1: Table of sensors and extracted features.

These cues were further segmented, dividing data into 30-seconds long intervals to processed by segmentation functions. The length of 30 seconds was empirically set as a trade-off following the Heisenberg uncertainty principle [52]. As a result, the dataset was divided into 57 blocks of attention and 74 blocks of distraction, as shown in the tab. 8.2.

Data	Value
Number of all segments	131
Attention segments	57
Distraction segments	74

Tab. 8.2: Overview of segmented blocks.

These blocks were then further processed by statistical calculations of suprasegmental features, referring to the literature [53]. These features include the basic statistical measures as mean, median, standard deviation, and others mentioned in the tab. 8.3, which estimates the characteristics of individual signals.

Suprasegmental features	
Mean	Median
Standard deviation	Relative standard deviation
Maximum	Max position
Minimum	Min position
Range	Relative range
Relative max	Relative min
Relative max position	Relative min position
Slopes	Kurtosis
Skewness	Percentiles
Linear regression coeficients	Linear regression error
Pearson's skewness coefficients	5th and 6th moment

Tab. 8.3: List of suprasegmental features. [53]

8.2 RUSBoost classifier

Following the previous section, the individual signals were coded by suprasegmental features. Afterward, the RUSBoost algorithm was applied with five-fold cross-validation. RUSBoost represents the optimal machine learning classifier algorithm for this type of data. The accuracy rate of individual features and their combination are presented in the following tables 8.4 and 8.5, respectively.

Individual features	Accuracy
Eye tracking system	83.2 %
Inertial sensor	67.9 %
Wristband	68.7 %

Tab. 8.4: Accuracy of the RUSBoost algorithm for individual features.

The results of the RUSBoost algorithm show that the eye-tracking system achieved the highest accuracy rate, 83.2 %, from all individual sensors. Compared to other sensors, the accuracy rate of the separate inertial sensor and separate wristband achieved almost 70 %, both. It means that data only about hand and head position can be regarded as promising for evaluating attention and distraction. Then, a combination of the wristband and headset inertial sensor features achieved an accuracy of 77.1 %. This means that they are only slightly less accurate than the eye-tracking system itself. Table 8.5 summarized also other combinations. The largest possible combination of all features leads to an accuracy rate of 87 %.

Combined features	Accuracy
Eye tracking system, Inertial sensor, Wristband	87.0 %
Eye tracking system, Inertial sensor	87.0 %
Inertial sensor, Wristband	77.1 %
Eye tracking system, Inertial sensor	84.0 %

Tab. 8.5: Accuracy of the RUSBoost algorithm for combined features.

The performance of a RUSBoost model at all classification thresholds is represented by a receiver operating characteristic (ROC) curves, shown in fig. 8.1 and 8.2. The graphs show the parameters of true positive (TP) and false positive (FP) rates. Area under the ROC (AUC) curve provides an aggregate measure for performance across all classification thresholds. The expected results match the accuracy rate given for each feature.

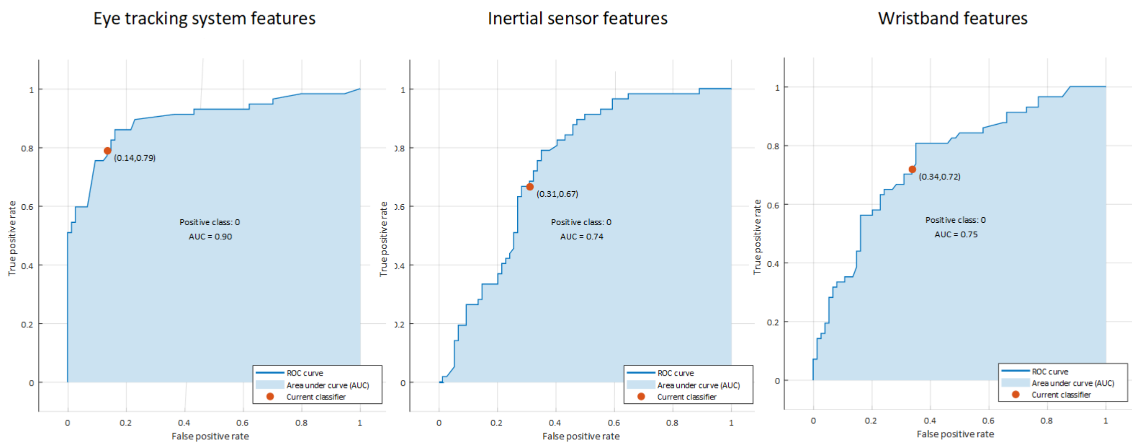

Fig. 8.1: ROC of individual sensors features.

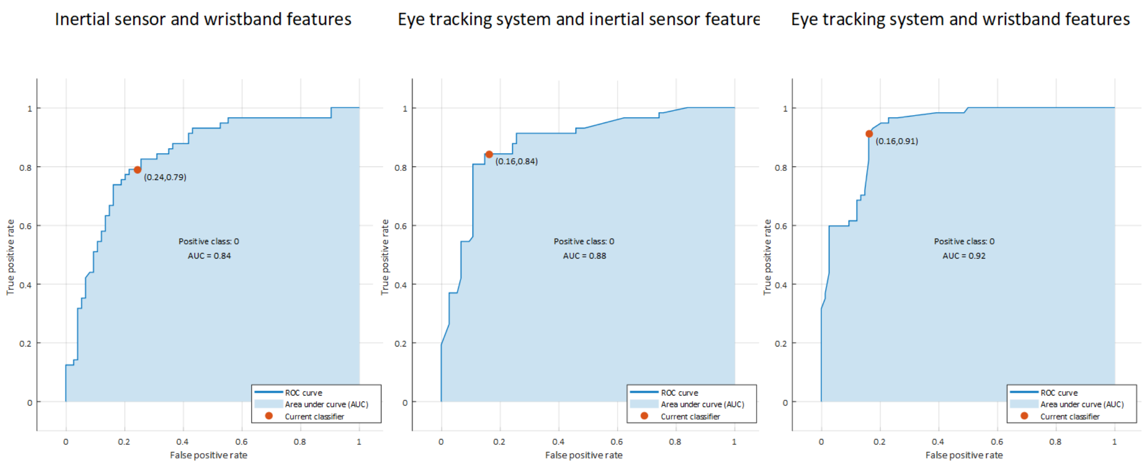

Fig. 8.2: ROC of combined features from multiple sensors.

9 CLIPS-based pilot inattention detection system

The use of an expert system presents an alternative approach to the machine learning method. While machine learning is based on inferring the data it has been exposed to, an expert system draws inference on the observed data. First, it is necessary to determine for what purpose the expert system will be used. In this case, the expert system is integrated into the application of the pilot inattention detection system, shown in fig. 9.1. This application includes parametrization of data from sensors, inference engine formed by an expert system, and decision making. Among other things, the use of the expert system brings significant benefits in terms of data collection requirements. At this stage, a large amount of training data is not required. Only a validation dataset is needed, on which the system function is verified.

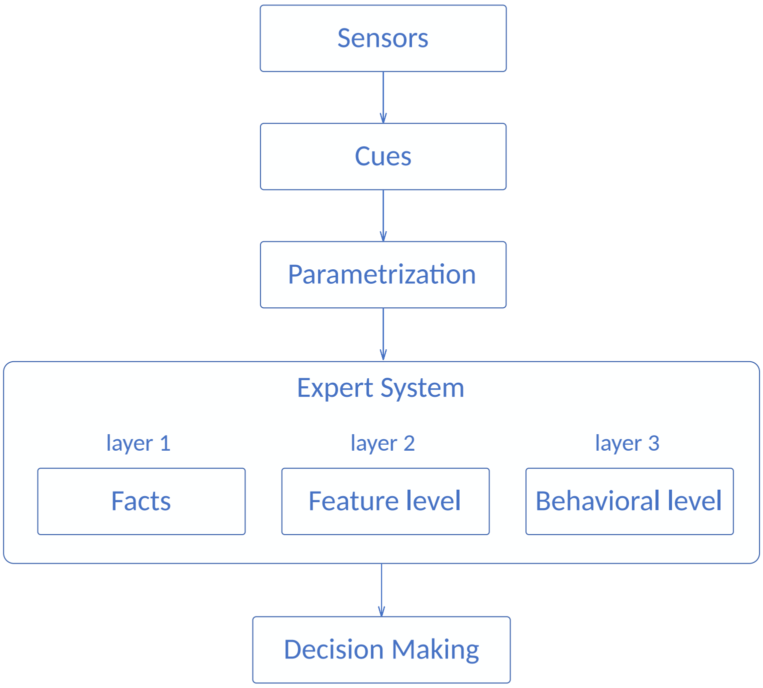

Fig. 9.1: Block scheme of the pilot inattention detection system.

When designing an inattention detection system based on an expert system, it is essential to define the set of facts and rules acquired from the knowledge base of some expert. The primary role of the expert system is to describe the behavior of the pilots from basic facts derived from the nature of the sensors. The list of input facts is formed from parameterized data. Subsequently, the fact list is asserted to the expert system environment. The task of the expert system is to imply new facts from defined ones using multiple rules. These retrieved facts are divided into two layers, depending on the stage of rule chaining. The output is a set of feature and behavioral facts. These are further evaluated in decision making.

9.1 Cues parametrization

As a first step, it is essential to convert the numeric data from the sensors to readable symbolic facts, as shown in fig. 9.2. This parameterization is in most cases clearly defined and can be done based on observations (e.g., heading, pitch and roll). Though, some of the measured cues need preprocessing. This is a case of fixations and saccades, where statistical evaluation is required. Another example is the voice activity, which is detected using a spectral energy-based voice activity detector. All data are evaluated over a separate time window of pre-defined length.

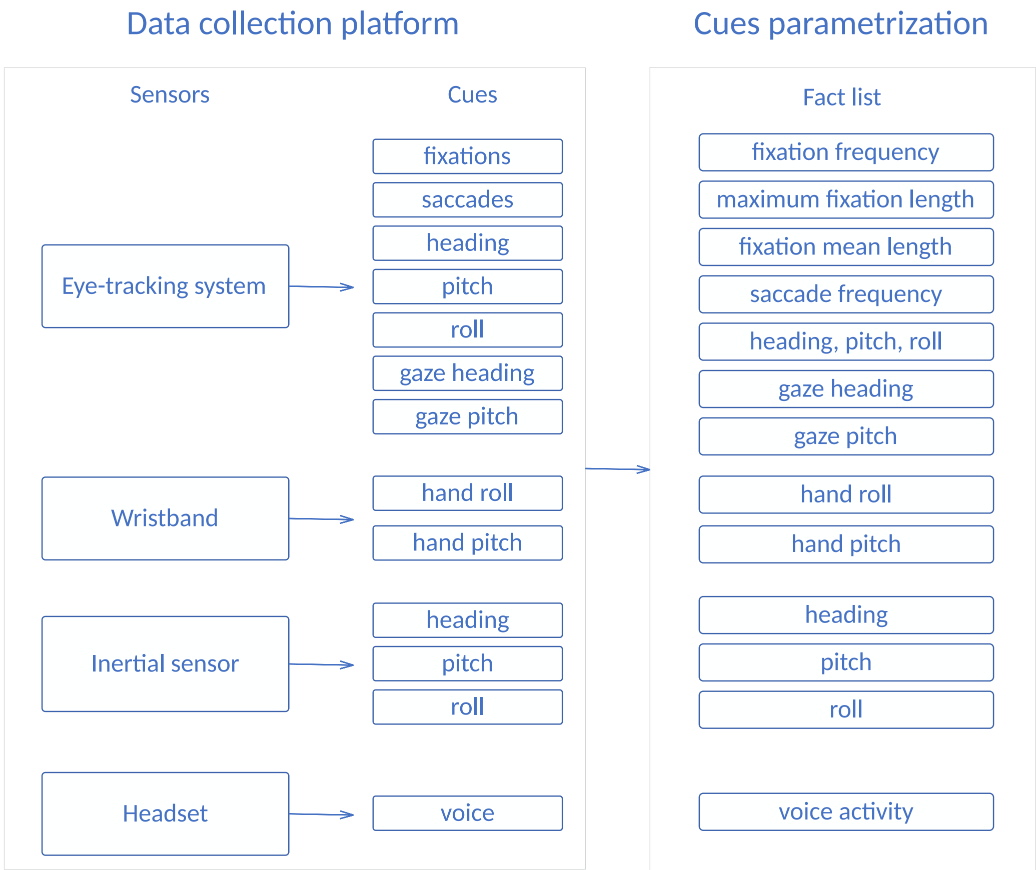

Fig. 9.2: The data obtained from the sensors and their corresponding facts.

9.1.1 Eye-tracking system

First, the data from the eye-tracking system were parametrized. Head and eye position have been clearly defined by their nature and they are evaluated as a mean value of the sampled data over a time window. The length of this window was set to one second to capture the rapid changes. However, this time window can be adjusted. The eye-tracking facts are listed in the tab. 9.1.

Head heading	Head pitch	Head roll	Gaze heading	Gaze pitch
left	down	left	left	down
center	neutral	neutral	center	neutral
right	right	right	right	right

Tab. 9.1: Facts arising from the movement of the head and eyes.

Other cues from the eye-tracking system, fixations, and saccades, are binary values and require preprocessing. Fixations and saccades are two characteristic quantities directly related to the amount of attention. Fixation refers to the act of fixating, which is the point between two saccades. According to the literature [54], fixation duration and its maximum duration indicate increases in cognitive processing load. Fixation times between 200 ms to 600 ms show the optimal fixation duration for perceiving information [17]. This range might be divided into short and long fixations, depending on the performed activity, shown in the tab. 9.2. Furthermore, a fixation frequency is derived from a technical report [55], which deals with the fixation frequency of the airline pilots. The experimental measurement from this report found the average fixation in the range from 65 to 140 per minute as optimal for instrumental flights.

Mean fixation duration		Maximum fixation duration		Fixation frequency	
too short	< 80 ms	optimal	< 600 ms	low	< 65
glance	80 - 200 ms	long	600 - 1300 ms	optimal	65-140
short gaze	200 - 400 ms	too long	> 1300 ms	high	>140
long gaze	400 - 600 ms				
stare	600 - 1300 ms				
too long	> 1300 ms				

Tab. 9.2: Facts derived from fixations and their ranges. Mean fixation duration (ms), maximum fixation duration (ms), fixation frequency (per minute)

As well as fixation, saccades are also crucial for estimating the pilot's attention. The experimental measures from literature [16], compares the frequency of saccades for experienced and inexperienced IFR pilots during ILS and NDB approaches. The measured data show that the mean frequency during ILS approaches reaches 148 saccades per minute for experienced pilots and 112 for inexperienced, respectively 138 and 98 for NDB. Although the design of the system assumes operation not only when landing, the ranges required some level of generalization. However, it still applies that the number of saccades per minute indicates the pilots' experience. More experienced pilots receive information in a shorter time and they are able to perform more saccades with shorter fixations. Based on knowledge it is possible to determine the ranges for frequency of saccades, as tab. 9.3 makes clear.

Saccade frequency (per minute)	
low	< 80
inexperienced pilots	80 - 113
optimal	113 - 131
experienced pilots	131 - 146
high	> 146

Tab. 9.3: Facts derived from saccades. Frequency of saccades (per minute).

9.1.2 Wristband

The data from the wristband includes a numeric value of Euler angles for all spatial coordinates. The first axis refers to the rotation of the hand, called supination or pronation. From this angle, it is possible to deduce whether a person is holding an object or the hand is placed freely. The second axis describes the terms of hand elevation and depression. From this data, it is possible to deduce the height of the hand and whether the pilot, for example, controls the overhead panel for activating the autopilot. The third angle is a measure of moving the hand away from the body. Another valuable piece of information is the actogram, which is the maximum value of the first derivative of all three axes, indicating the value of motion changes. This parameter indicates whether the activity involves fine motor skills or expressive gestures. Facts arising from the hand are illustrated in fig. 9.4.

Hand heading	Hand pitch	Actogram
left	down	calm
center	neutral	moderate
right	slightly up	intense
	up	

Tab. 9.4: Facts arising from the movement of the hand.

9.1.3 Inertial sensor

The inertial sensor indicates the value of the Euler angle, similar to the inertial sensor in the wristband. These three angles are heading, pitch, and roll. Individual facts are defined similarly to the eye-tracking system, as shown in fig. 9.5. The advantage of using this sensor is the case when the camera does not capture a person with sufficient quality. It can happen if the pilot turns away from the camera.

Head heading	Head pitch	Head roll
left	down	left
center	neutral	center
right	up	right

Tab. 9.5: Inertial sensor fact list.

9.1.4 Microphone

The audio recording of the pilot's voice requires the data parameterization as every other sensor. First, it is essential to detect if the segment contains a voice. For this purpose, the voice activity detector based on spectral-domain energy is used. The whole algorithm is described in the literature [56] and shown in fig. 9.3. Spectral-domain enables the calculation of the energy distribution over frequencies. Audible sound is assumed to be present at lower frequencies between 20 Hz and 20,000 Hz. This condition provides a good criterion to determine the human voice regions. The output is binary information whether voice activity is present. The voice fact gives the information about the percentage of speech contained in the time segment. Based on observation, three categories of activities were determined: low ($< 10\%$), moderate ($10 - 30\%$), and high ($> 30\%$).

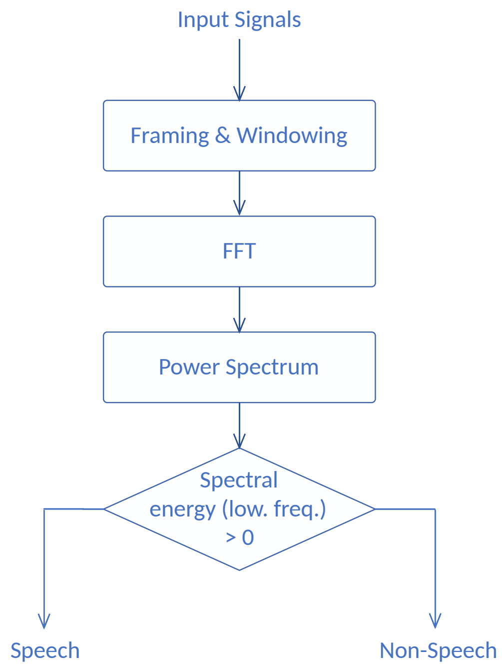

Fig. 9.3: Block scheme of the spectral energy-based voice activity detection. [56]

9.2 Inference engine

An essential part of the expert system is the knowledge base. In this case, the knowledge is gained from the discussion with pilots, human factor expert, from literature, and by observations. The expert knowledge is summarized in a set of rules that is easy to understand and whose basis can be modified or added (example is attached in the appendix). The rules imply new facts, which describe more precisely the activity of the pilot and they are divided into two layers:

- feature layer
- behavioral layer

The first feature layer is formed by the rules that evaluate the activity based on basic sensor facts. These features give more sense of the pilot activities than the individual abstract sensor facts. It is, for example, the primary evaluation of attention, the direction of view, and speech activity. However, these activities may be considered as attention in a specific context but as inattention in another. Therefore, a higher layer is designed, which specifies activities on a behavioral basis. Applying new rules derive new implied behavioral facts. These already specify certain activities, which lead to attention or distraction, as shown in tab. 9.6.

Feature level fact/rule	
Looking away	look out the window or up and not scan the instruments
Conversation	moderate or high voice activity
Attention tunneling	one of the adverse conditions occurs, either too long fixation or too low frequency of saccades
Attention focusing	optimal fixation frequency and duration without adverse effects
Experienced behavior	saccades frequency corresponding to the experienced pilot with short gazes without adverse effects.
Behaviour level fact/rule	
Visual distraction	too long gazes during looking out of the window
Instrument scanning	pilot's head and gaze are straight or slightly down and pilot performs optimal fixation frequency and without long stare
Crew conversation	conversation with looking right on the copilot or passenger
Factual conversation	low or moderate voice activity without long fixation by looking away indicating either factual conversation of the pilot or ATC communication
Reading	the pilot is holding an object and his hand and gaze are slightly down
Gestures	hand movements are too expressive
Joystick manipulation	gentle hand movements with full attention

Tab. 9.6: An overview of all rules included in the expert system.

9.3 Decision making

The last element of the pilot inattention system is decision making. The result of the expert system is a list of feature and behavior facts, which are given either penalties or rewards. These points are assigned based on the importance of the activity. It should be stated that the points reported in tab. 9.7 is also a subject for fine-tuning after an appropriate evaluation with a human factor expert. The result of the pilot inattention detection system presents the inattention score, which is a cumulative sum over 30-second long time window.

Evaluated fact	Penalties/Rewards
Instrument scanning	+3
Experienced behavior	+2
Environment scanning	+1
Visual distraction	+1
Joystick manipulation	+1
Factual conversation	+1
Attention focusing	+1
Attention tunneling	-1
Crew conversation	-1
Auditory distraction	-1
Reading	-1
Gestures	-1

Tab. 9.7: Corresponding penalties and rewards for the dictionary of activities

9.4 Evaluation

The pilot inattention detection system was evaluated on collected data performed in chapter 7. Compared to the previous machine learning approach, the state is indicated by a continuous score, as illustrated in fig. 9.4 and 9.5. The score range between -100 and 100, when the positive values present attention and the negative ones inattention. As it can be seen, the attention curve does not correspond exactly to the scripted scenario. However, it is possible to calculate the accuracy, which achieves 74 % as an average for all sessions, as shown in tab. 9.8. Since the system has set rules for the behavior of professional pilots, it is not possible to perceive this information as a reliable evaluation without the data from professional pilots.

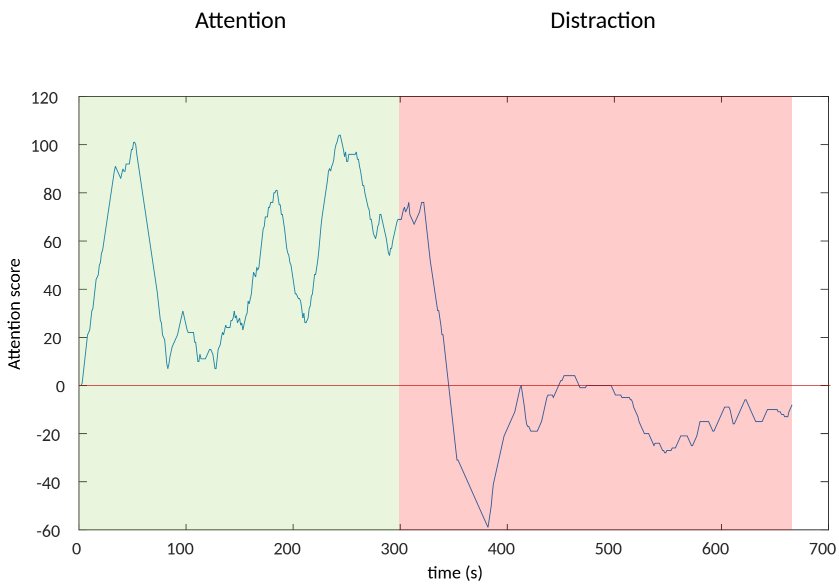

Fig. 9.4: Attention curve of participant no. 1.

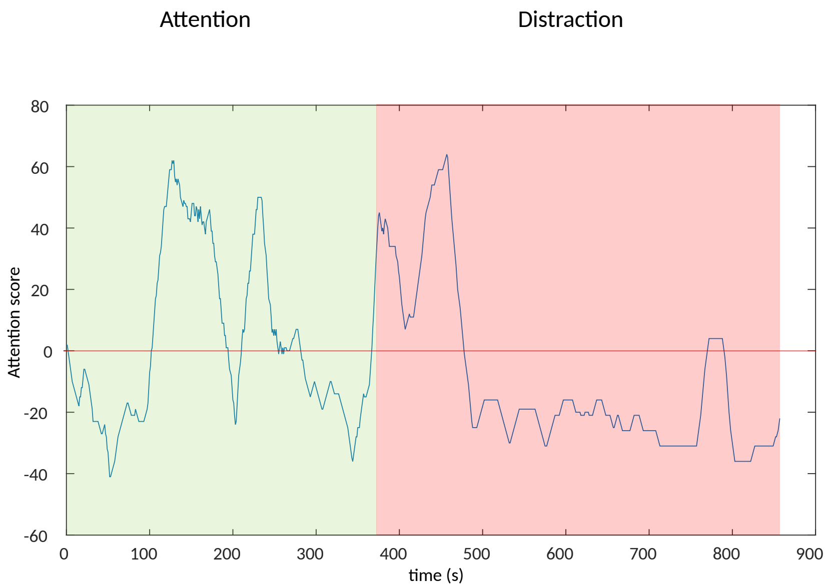

Fig. 9.5: Attention curve of participant no. 4

From the so-called attention curves illustrated above, it is shown that the attention score fluctuates. The inattention drops were caused due to limited experience of participants. The area of distraction also occasionally contains attention. This error occurred mainly in activities that show similar characteristics. An example could be reading confused by instrument scanning or distractive conversation confused by factual conversation.

Session number	Accuracy
1	92 %
2	68 %
3	77 %
4	65 %
5	68 %
Mean	74 %

Tab. 9.8: Comparison of accuracy of pilot inattention system for all sessions.

9.5 Demonstration platform

The following platform was designed to demonstrate the results of the pilot inattention detection system. The platform was developed in the Qt framework [57], using QML as a declarative language for user interface application design. The demonstration platform displays the list of facts and their inferences within the expert system. These facts are divided into input, feature, and behavior layers, as shown in fig. 9.6. Concurrently, the platform displays the attention curve and the attention score. Color differences present the activity of the expert system. In the column of input facts, only those that are present are displayed in blue color. The feature and behavior columns already list all possible facts that can occur. Those that are not triggered are marked gray. Facts that lead to attention are colored green. On the contrary, the distraction leading facts are red. At the top left is located a graph of the inattention curve over time. At the bottom right is presented the attention score, a circular progress bar that changes color according to the score level, either green for attention or red for distraction. The function of the platform is to demonstrate the inferences of an expert system and a decision making mechanism. This application offers a tool for understanding the relationship between different layers of facts and can be used to further tuning the expert system.

Fig. 9.6: Demonstration platform of inattention detection system.

Conclusion

The goal of this master thesis was to design a pilot inattention detection system. In this work, two approaches were proposed. The first approach was based on a data-driven system by employing a RUSBoost classifier and a set of features from multimodal cues. The second approach was based on an expert system, presented by CLIPS-based pilot inattention detection system.

As a first step, it was essential to specify the target aviation sector, which is general aviation. This sector is more prone to human errors. General aviation includes two main flight rules, namely IFR and VFR. In this work, it was decided to cover only IFR. The main reason was that IFR pilots are at greater risk of inattention. The activity of the IFR pilot consists of piloting an aircraft based only on flight instruments. It means that IFR is more demanding on pilot attention than VFR.

Next, the literature review revealed several methods for monitoring attention. The vast majority of the reviewed work used eye-tracking features. Studies showed that an eye-tracking system is the most significant indicator of pilot inattention. Among the most important eye cues belong fixations, saccades, and gaze direction. Besides the visual distraction, research also dealt with biomechanical distraction (reading, using portables) and proposed detection method by employing image processing. In general, studies suggested two possible approaches for inattention detection, including supervised machine learning methods and rule-based algorithms.

The work presented in this thesis starts with a selection of sensors, namely an eye-tracking system, smart wristband, omnidirectional microphone, and a headset with an inertial sensor. These sensors provide behavior data about pilot's head position, eye features, hand position, and voice activity. The data collection took place in a static simulator and included a scripted scenario for participants with basic aviation knowledge. The protocol incorporates two blocks, namely attention and distraction. The collected data was further analyzed and used for a data-driven system and rule-based evaluation system.

For the data-driven system, the RUSBoost classifier was chosen. RUSBoost belongs to the category of decision tree algorithms and its use is suitable for good explainability. The prior assumption that the eye-tracking system as an individual modality achieves the best performance has been confirmed. However, it should be stated that the goal was not to reach the highest accuracy at the cost of using multiple sensors since it can be hard to integrate this system into the real aircraft.

Especially, integration of the eye-tracking camera can be challenging. Therefore, it was important to determine the usability of other sensors, which are more integrable and cost-effective comparing to the eye-tracking system. The suggested combination of the inertial sensor with the smart wristband can achieve promising results. The initial intention was to continue in data collection. However, this activity was stopped due to the pandemic situation and it was not possible to further develop machine learning methods.

The second proposed system for pilot inattention detection was based on an expert system. Comparing to machine learning, the rule-based system requires an expert who designs rules based on his/her knowledge. Several proposals of rules were found in the relevant works. These include researches mentioning the relation between eye features and attention. The rule-based system required converting the numerical input data to symbolic notation using statistical parameterization within a specified time window. Parameterization of data from sensors involved segments of different lengths, which were subsequently combined for expert system purposes. The inference engine of the expert system implied new facts based on defined rules. These facts include information about features and activities, which lead to attention or distraction. These features and activities were scored within the 30-second moving window. The result of the system is the attention score, which varies in negative values for inattention and in positive values for attention. Based on collected data, the pilot detection system was evaluated. It has been found that the system achieved different results compared to machine learning. This was since the rules were set for experienced pilots. In participants' performance, attention drops occurred due to lack of knowledge and poor orientation in the cockpit. However, using the rule-based pilot detection system is beneficial due to its explainability and transparency for further tuning. The indisputable advantage is also that other experts can contribute to further expanding the knowledge base of the expert system.

The next step of the work would be to improve the performance of machine learning algorithm, which is conditioned by the collection of a larger amount of data. Improving the expert system-based approach could continue by incorporating additional facts and rules. To this end, it would also be possible to employ machine learning or image processing in the parameterization of the input data, which could provide a more complex pilot inattention detection system.

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List of symbols, quantities and abbreviations

AdaBoost	Adaptive Boosting
AI	Artificial Intelligence
ANC	Aviate, Naviage, Communicate
ATC	Air Traffic Control
AUC	Area under the ROC Curve
CLIPS	C Language Integrated Production System
DC	Distraction Calculation
DDM	Distraction-decision Maker
EDA	Electrodermal Activity
ELM	Extreme Learning Machine
EOFR	Eyes off forward roadway
FMS	Flight managment system
FN	False Negative
FP	False positive
FPR	False Positive Rate
GA	General Aviation
GPS	Global positioning system
HR	Heart Rate
HRV	Heart Rate Variability
I2C	Inter-Integrated Circuit
ICAO	International Civil Aviation Organisation
IFR	Instrument Flight Rule
ILS	Instrument Landing System
IMC	Instrument meteorological condition

LOOCV	Leave-One-Out Cross-Validation
MDD	Multidistraction Detection
ML	Machine Learning
NDB	Non-directional Beacon
PFD	Primary Flight Display
PPG	Photoplethysmogram
PRC	Percentage Road Center
PWM	Pulse Width Modulation
ROC	Receiver operating characteristic
RUSBoost	Random Undersampling Boosting
RVSP	Risky Visual Scanning Pattern
SA	Situation Awareness
SVM	Support Vector Machine
TN	True Negative
TP	True positive
TPR	True Positive Rate
USB	Universal Serial Bus
VFR	Visual Flight Rule
VMC	Visual meteorological condition

A Example of rules for the expert system

```
(defrule look-off
   (or(heading-left)
      (heading-right)
      (gheading-left)
      (gheading-right)
      (pitch-up)
      (gpitch-up))
   (not(instrument-scanning))
=>
(assert (look-off)))


(defrule visual-distraction
      (look-off)
      (or(gaze-long)
         (stare)
         (fixation-toolong))
=>
(assert (visual-distraction)))


(defrule attention-tunneling
      (or(fixation-toolong)
         (saccades-toolowfr)
         (stare)
         (fixation-toolongmean))
       (not(glance))
       (not(gaze-short))
       (not(gaze-long))
       (not(instrument-scanning))
=>
(assert (attention-tunneling)))

(defrule instrument-scanning
      (not(look-off))
      (not(attention-tunneling))
      (or(gaze-short)
         (gaze-long)
         (glance))
```

```
      (or(gaze-straight)
         (gaze-down)
         (gaze-center))
      (not(or(hand-right)
             (hand-left)))
      (fixation-optimalfr)
      (not(saccades-toolowfr))
      (not(reading))

=>
(assert (instrument-scanning)))

(defrule attention-focusing
      (or(fixation-optimalfr)
         (fixation-highfr))
      (fixation-optimallength)
      (not(attention-tunneling))
=>
(assert (attention-tunneling)))

(defrule conversation
      (speech-moderateactivity)
      (speech-highactivity)
=>
(assert (conversation)))

(defrule crew-conversation
      (conversation)
      (or(heading-right)
         (heading-left))
=>
(assert (crew-conversation)))


(defrule reading
    (or(hand-right)
       (hand-left))
    (or(pitch-down)
       (pitch-center)
       (gpitch-slightlydown)
       (gpitch-down))
```

```
   (not(hand-up))
   (not(look-off))
   (not(instrument-scanning))
   (not(factual-conversation))

=>
(assert (reading)))



(defrule environment-scanning
    (look-off)
    (or(gaze-short)
       (glance))
    (not(reading))
    (not(attention-tunneling))
    (not(instrument-scanning))
    (not(visual-distraction))
=>
(assert (environment-scanning)))

(defrule joystick-manipulation
   (or(hand-calm)
       (hand-moderate))
   (or(hand-center)
      (hand-down))
   (or(hand-left)
      (hand-right))
   (not(reading))
   (not(gesture))
   (attention-focusing)

=>
(assert (joystick-manipulation)))
```

Listing A.1: Listing example of rules from the CLIPS expert system.